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Dead Band Zone Model Predictive Control of Cut Tobacco Drying Process

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ABSTRACT In this article, an L1-Norm model predictive controller with a dead band zone is proposed for the cut tobacco drum dryer system. The control objective is to make the drum dryer temperature, hot air temperature and cut tobacco outlet temperature meet the process constraints, and optimize the outlet moisture content of the cut tobacco. First, the cut tobacco drum dryer system is introduced, and the nonlinear open equation model is established. Then an L1-Norm moving horizon estimator (MHE) is designed to provide state and parameter estimation for the controller by using its ability to deal with nonlinearity and constraints. A model predictive control (L1-Norm zone MPC) for L1-Norm target tracking with a dead band zone is proposed for the cut tobacco drum dryer system. The simulation results show that the proposed L1-Norm zone MPC (L1-ZMPC) better-tracking performance and the controller's minimum action economic characteristics compared with the traditional setpoint tracking model predictive control.

INDEX TERMS Cut tobacco drum dryer system, moving horizon estimation, model predictive control, nonlinear system, parameter estimation, state estimation.

I. INTRODUCTION

Drying aims at reducing the moisture content within a product by application of thermal energy to produce dried products of desired attributes [1]. As one of the most energy-consuming unit operations in the industry, drying energy consumption accounts for about $10\% - 25\%$ of the national industrial energy consumption. The drying operation in the tobacco industry does not merely remove the moisture content because many quality factors can be adversely affected by the incorrect selection of drying conditions and drying equipment. The consumer acceptability, appearance, and organoleptic properties are the desirable properties of high-quality tobacco [2]. Cut tobacco drum dryers are one of the most commonly used drying equipment in the industrial scale, which is usually used in the chemical engineering and food processing industry. Drum drying is a complex process involving simultaneous heat and mass transfer phenomena, coupled with the movement of solid particles and air within the drum dryer [3], [4]. Also, it is well known that most industrial dryers are less energy efficient, from a disappointing 10% to a respectable 60% (this ratio is defined as the theoretical energy required for the drying to the actual energy consumed). Therefore, due to the rising cost of energy and the increasingly fierce global competition, these performances must be improved. Besides, most research is still focused on understanding drying mechanism and product quality, rather than the control of operation itself. Simultaneously, it must be noted that the main cost of the dryer is not in the initial investment (design and assembly), but in daily operation, control is crucial for energy-saving and obtaining ideal product quality [5]–[7].

One common control strategy adopted in the control of cut tobacco drum dryer system is the classical proportional–integral–differential (PID) control [1], [3], [8]. There is no single controller that can be applied to all dryers due to the global use of 60000 drying products and 100 dryers, and the complexity of transport phenomena in the drying process. In the literature, different advanced control strategies are also studied, including the design of fuzzy controller for natural drying process [9], the design of internal model controller (IMC) in a continuous infrared dryer [10], and

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the design of MPC control in different dryers [5], [11]–[13]. Nevertheless, the above control algorithms MPC and PID are designed based on the linear dynamic model or approximate linear model of the drying system. Model predictive control (MPC), also referred to as moving horizon control or receding horizon control, has become an attractive feedback strategy, especially linear processes. MPC can solve some important problems, such as online calculation, the interaction between modeling/identification and control, and system theory stability. However, many systems usually have inherent nonlinearity. This, coupled with higher product quality specifications and increasing productivity requirements, more stringent environmental regulations, and economic considerations of process industry requirements, requires operating systems to be closer to the permitted operating areas' boundaries. In these cases, the linear model is often not enough to describe the process dynamics, so the nonlinear model must be used. This promotes the application of nonlinear model predictive control [14].

In the cut tobacco drying process is a complex nonlinear thermodynamic system. Several factors make the optimal operation of this process challenging. First, the moisture at the outlet of the cut tobacco is controlled by the drum dryer temperature and the hot air temperature, and there is no direct operation input, which is a weak control; second, there is a strong coupling between the drum dryer temperature, cut tobacco outlet temperature, and hot air temperature. Anyone temperature cannot be well controlled, and the other two temperatures are greatly affected. The nonlinearity of the system and the typical wide operating range also exacerbate operational challenges. In the cut tobacco drying process, the primary task is to meet the cut tobacco's outlet moisture content. Under the condition of reducing the operation cost, as long as the cut tobacco outlet temperature, drum dryer temperature, and hot air temperature meet the process requirements, energy consumption can be saved. Motivated by these considerations and inspired by Hedengren *et al.* [15], Liu *et al.* [16], Mao *et al.* [17], and Zhang *et al.* [18], an L1-Norm MPC with a dead band zone tracking design is proposed for cut tobacco drum dryer system in this work. First, the studied cut tobacco drum dryer system with a production capacity of $500kg/min$ along with its fourth-order nonlinear open equation model are formulated. Then, an L1-Norm moving horizon estimator (MHE) is employed to provide state and parameter estimates for the subsequent controller design due to its distinct ability in dealing with system constraints and nonlinearities. Subsequently, a novel L1-Norm MPC with dead band zone tracking design is proposed to optimize the cut tobacco drying process. To achieve this, a dead band zone, which penalizes the distance between system output and the demand target zone, is incorporated into the existing MPC framework. The conventional tracking MPC (CMPC) is also introduced for comparison purposes. The simulation results under different scenarios have demonstrated that the proposed L1-Norm zone MPC (L1-ZMPC) provides a more flexible way to handle the cut tobacco drum dryer system's optimization problem in the presence of system nonlinearities, constraints, and disturbances.

The remainder of this article is organized as follows: a detailed description of the studied cut tobacco drum dryer system with a production capacity of $500kg/min$ along with its fourth-order nonlinear open equation model in Section 2; Section 3 introduces the design of L1-Norm MHE and conventional tracking MPC (CMPC), and Section 4 provides the design details of the proposed L1-Norm MPC with a dead band zone and NMPC stability. Extensive simulations have been conducted in Section 5 to verify the performance of the proposed L1-Norm zone MPC (L1-ZMPC) over conventional tracking MPC (CMPC) in setpoint tracking and disturbance rejection, especially weak control. Finally, we give conclusions in Section 6.

II. SYSTEM DESCRIPTION AND MODELLING

A. SYSTEM DESCRIPTION

In cigarette production, the dryer is not only important equipment for tobacco drying and expansion but also key equipment to determine the internal quality of cigarettes. The dryer's drying task: first, remove some moisture in the cut tobacco to meet the subsequent processing requirements. After heating and humidifying, cut tobacco's moisture content is more than 19%. It needs to be dried and dehumidified by the dryer to reduce the moisture content to $13\% - 15\%$, to meet the technological requirements of coiling. Second, improve and enhance the sensory quality of tobacco. Due to the large surface area of tobacco, in the drying process, the tobacco is treated by high temperature, part of the free nicotine and ammonia volatilization, the smoke's irritation will be reduced, and part of the impurities can be removed at the same time.

In this work, we consider a cut tobacco drum dryer system with a production capacity of $500kg/min$, as shown in Figure 1. The drum dryer uses steam as the heating energy and adopts the mixed drying method of conduction and convection to dry and dehumidify the cut tobacco, with conduction heating as the main and convection heating auxiliary. The heating steam heats the cylinder wall through the steam supply system of the dryer. The cut tobacco is fed into the continuously rotating dryer cylinder by the vibration conveyor, and the cylinder wall is in direct contact with the cut tobacco, which transmits the heat to the cut tobacco in the way of conduction. Simultaneously, the hot air flows in the tube from the feeding end to the cut tobacco. The hot air directly contacts the cut tobacco and transmits the heat to the cut tobacco by convection to strengthen the cut tobacco's moisture vaporization. After the cut tobacco absorbs heat from the cylinder wall and the hot air, the temperature rises, and the moisture vaporize on the surface of the tobacco, diffuses to the hot air flow, which absorbs water vapor and turns into the hot and wet air, and enters the air dust box from the discharge end of the dryer. When the exhaust gas comes out from the dryer, the exhaust gas's entrained material

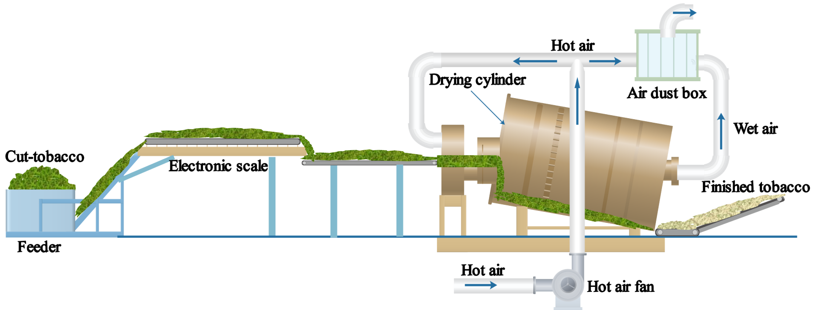

FIGURE 1. Schematic of cut tobacco drum dryer system.

must go through suitable dust collectors such as cyclones and baghouses to collect the entrained product and satisfy the exhaust discharge regulations. In the whole process, under the action of the heating wall and hot air, the cut tobacco will turn continuously with the rotation of the inclined cylinder, and then gradually slide down from the high end of the dryer to the discharge end.

B. DYNAMIC MATHEMATICAL MODEL OF CUT TOBACCO DRUM DRYER SYSTEM

For the convenience of calculation and testing, the following assumptions are made: the drum dryer is adiabatic (Heat loss Q_{l1} and Q_{l2} equal to 0), moisture movement and heat transfer are one dimensional; the drum length L is $7.7m$; the diameter is 1.25 m; the slope of drum dryer is 3.5 *degree*; the area is A, cross-area is $A1$, and the volume is V. No chemical reaction occurs during the drying process; that is, the thermal and chemical properties of the material, air and moisture are constant within the range of temperatures considered; the drying air is distributed uniformly through the dryer. The mass flow at the input and output of the drum dryer must be equal; otherwise, the mass and heat capacity of the system will change.

Table 1 specifies the inlet and outlet data of the drum dryer in operation, assuming that the speed of cut tobacco and hot air, the specific heat of cut tobacco, water, and air, and the quality of cut tobacco and hot air are always constant.

Mass balance equation for moisture in the cut tobacco is represented by equation 1:

$$\rho_p V \frac{dw}{dt} = \dot{m}_{in} w_{in} - \dot{m}_{out} w - \rho_p V R_{evap} \tag{1}$$

The drying rate of cut tobacco, R_{evap}, is an important parameter of the model. Drum dryer temperature is the direct reason for the drying of cut tobacco. The drum directly transmits heat to the cut tobacco through the heating wall and the heat exchange plate, so that the cut tobacco is fully heated and the moisture evaporates to dry. The mass flow and velocity of the hot air in the drum are fixed. The saturation degree of air in the drum is determined by the evaporation amount of cut tobacco and hot air temperature. When the drum dryer's speed and temperature are fixed, the evaporation amount depends on the hot air temperature. The drum's rotation speed determines the retention time (baking time) of the cut tobacco in the drying cylinder. The longer the baking time is, the more water evaporates. As the baking process is accompanied by chemical reaction to improve tobacco's internal quality, it needs a certain time, which should not be too short or too long. The higher the flow rate of hot air, the better the evaporation of moisture. When the moisture discharge valve is closed, the hot air stops supplying to the drum dryer. Although the air's moisture is still evaporating, the moisture in the air continuously returns to the humidified tobacco, forming the dynamic balance of moisture evaporation and humidification of cut tobacco. Although increasing the drum dryer temperature, hot air temperature, and reducing the drum dryer speed can not make the cut tobacco dry in the drum dryer. In this article, the rotation speed of the drum dryer and the hot air velocity is fixed. The direct drum dryer rotate at 11.6 *rpm*, hot air speed 0.3 *m/s*. R_{evap} only considers the influence of the drum dryer temperature and the temperature of the hot air on the moisture evaporation of tobacco.

TABLE 1. Inlet and outlet data of the cut tobacco dryer (operational data).

Property	Symbol	Data
Mass flow of cut tobacco (kg/min)	$\dot{m}_{in} = \dot{m}_{out}$	500
Volume flow of dry air (m^3/min)	q	2000/60
Specific heat of water liquid $(KJ/kg^\circ C)$	c_w	4.18
Specific heat of water vapor $(KJ/kg^\circ C)$	c_v	1.85
Specific heat of the dry air $(KJ/kg^\circ C)$	c_{air}	1.01
Specific heat of the cut tobacco $(KJ/kg^\circ C)$	c_p	1.83
Density of water (kg/m^3)	ρ_w	1000
Density of the air (kg/m^3)	ρ_{air}	1.293
Density of the cut tobacco (kg/m^3)	ρ_p	320
Inlet moisture content of the air	w_a	0.14
Inlet moisture content of the cut tobacco	w_{in}	0.19
Outlet moisture content of the cut tobacco	w	0.14 ± 0.005
Inlet speed of the air (m/s)	v_a	0.3
Air inlet of temperature $(^\circ C)$	T_{in}	20
Inlet temperature of the cut tobacco $(^\circ C)$	T_{pin}	30
Outlet temperature of the cut tobacco $(^\circ C)$	T_{pout}	$20-60$
Hot air temperature $(^\circ C)$	T_1	$100-110$
The temperature of drum dryer $(^\circ C)$	T_{dryer}	$150-160$

$$R_{evap} = 0.0001649 exp\left(\frac{2T_{dryer} + T_1}{T_1}\right) \tag{2}$$

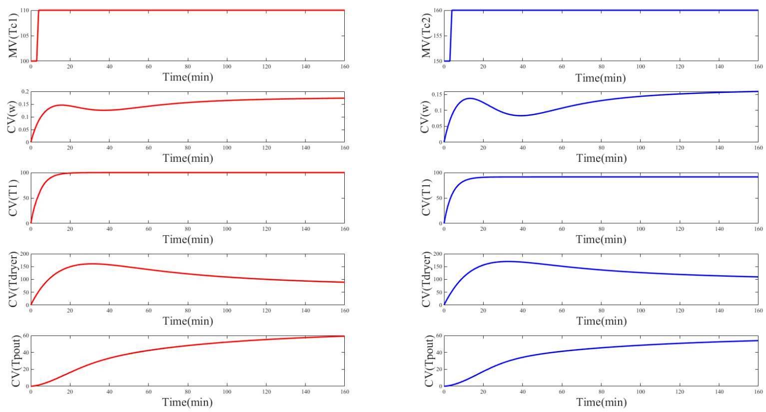

FIGURE 2. Cut tobacco drum dryer system step test.

Energy balance equation for temperature in the heater and dryer are represented by equation 3, 4, 5:

$$\begin{aligned}\frac{dT_{dryer}}{dt} &= \frac{\rho_{air}c_{air}q\left(T_{in}-T_{dryer}\right)}{\rho_{mix}Vc_{mix}}+\frac{\dot{m}_{in}c_p\left(T_{pin}-T_{pout}\right)}{\rho_{mix}Vc_{mix}} \\ &\quad+\frac{\rho_p V R_{evap}c_w\left(T_{pin}-T_f\right)}{\rho_{mix}Vc_{mix}}+\frac{Akeff\left(T_{c2}-T_{dryer}\right)}{L\rho_{mix}Vc_{mix}}-Q_{l2}\end{aligned} \tag{3}$$

$$\begin{aligned}\frac{dT_{pout}}{dt} &= \frac{Akeff\,1\left(T_{dryer}-T_{pout}\right)}{L\rho_p Vc_p}+\frac{Akeff\,1\left(T_1-T_{pout}\right)}{L\rho_p Vc_p} \\ &\quad-\frac{\rho_p V R_{evap}c_w\left(T_{pout}-T_{pin}\right)}{\rho_p Vc_p}\end{aligned} \tag{4}$$

$$\frac{dT_1}{dt} = \frac{\rho_{air}c_{air}q\left(T_{in}-T_1\right)}{\rho_{aw}Vc_{aw}}+\frac{A_1keff\,2\left(T_{c1}-T_1\right)}{L\rho_{aw}Vc_{aw}}-Q_{l1} \tag{5}$$

ρ_{mix} and c_{mix} are the mixing density and mixing specific heat capacity in the drum, ρ_{aw} and c_{aw} are the mixing density and mixing specific heat of air and water in the heater. $keff = 100$, $keff\,1 = 5$, $keff\,2 = 700$ are all thermal conductivity $(W/m°C)$; here, they were considered constant along the time; in the following nonlinear dynamic estimation section, these three parameters will be estimated.

Model validation is accomplished through dynamic parameter estimation. The parameter estimation experiment was similar to a step test. We verify the established transient model of cut tobacco drying through a step test, as shown in Figure 2. Simultaneously, the step test brings a beneficial analysis of the subsequent dynamic estimation and control. Compared with the cut tobacco dryer system's operational data, the results show that the proposed model can be used within an acceptable error range.

Two common manipulated variables are the steam temperature T_{c1} of the heater and the heating steam temperature T_{c2} of the drum dryer. Let us define the state vector as $x = \left[w\ T_{dryer}\ T_{pout}\ T_1\right]^T$, the manipulated input vector as $u = \left[T_{c1}\ T_{c2}\right]^T$, and the process output vector as $y = \left[w\ T_{dryer}\ T_{pout}\ T_1\right]^T$, a set of parameters $p = \left[keff\ keff\,1\ keff\,2\right]^T$, d is a time varying trajectory of disturbance values. output functions, equality and inequality constraints are represented by f, g, and h, respectively. Then the dynamic mathematical model of cut tobacco drum dryer system can be described by a compact nonlinear open equation form model as follows:

$$\begin{aligned}0 &= f\left(\frac{dx}{dt},x,y,p,d,u\right) \\ 0 &= g(x,y,p,d,u) \\ 0 &\leq h(x,y,p,d,u)\end{aligned} \tag{6}$$

Constraints dealing with process limitations (e.g., actuators magnitude have upper and lower bounds), process safety (e.g., a maximum temperature threshold beyond which operation becomes hazardous), process specification (e.g., a maximum is known surface temperature beyond which final quality is too altered) may be explicitly incorporated into this formulation (g and h).

III. NONLINEAR DYNAMIC ESTIMATION AND CONVENTIONAL TRACKING MPC

In this section, we introduce MHE and conventional tracking MPC (CMPC). We propose using MHE for states and parameter estimation purposes since it can handle nonlinear systems and take into account constraints [19]–[24]. The conventional tracking MPC (CMPC) will be compared with the proposed L1-norm MPC with dead band zone tracking. The MHE and MPC structure considered in this work are represented in figure 3.

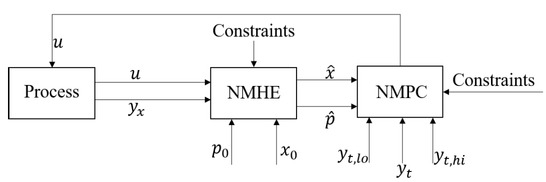

FIGURE 3. MHE and MPC structure.

A. NONLINEAR DYNAMIC ESTIMATION OF MHE

State estimation and parameter estimation have been applied in the chemical process industry. Examples of industrial applications include offline and online process system identification, parameter estimation for model predictive control and process disturbance prediction. Some states of the system can not be measured directly, or the cost of direct measurement is too high, so it is necessary to estimate these states according to the output measurement of the system. For the cut tobacco drum dryer system, the measurable outputs are hot air temperature T_1, drum dryer temperature T_{dryer} and cut tobacco outlet temperature T_{pout}, while the cut tobacco outlet moisture w is not measured. Three parameters $keff$, $keff1$ and $keff2$ are estimated simultaneously. In the proposed L1-norm zone MPC design, the whole system states and parameters are needed, which makes the design of state and parameter estimator necessary.

According to the different estimation time domain, moving horizon estimation can be divided into full information state estimation and approximate moving horizon estimation. Full information state estimation uses all the measurement information to estimate the system's initial state and the disturbance acting by minimizing the optimization problem's performance index and calculating the system state's estimated value from the system dynamic equation. The estimation results are accurate because of the large amount of information and the ability to estimate the system's disturbance. However, with the increase in time, more and more data are processed, leading to an unsolvable problem. Rao and Rawlings [19] and Rao *et al.* [20]introduced a fixed time domain N to divide the calculation time domain of the optimization problem into two parts. By introducing the arrival cost function, the full information moving horizon estimation problem is transformed into a fixed time-domain estimation problem, to avoid the problem that the amount of computation increases with time. However, the arrival cost function calculation is complex, and there may be no analytical solution for the constrained system. To ensure the solvability of the estimation problem, Hedengren *et al.* [21], Spivey *et al.* [22], and Hedengren and Eaton [24] proposed a new MHE method, which overcomes some of the limitations of the squared error MHE approach.

The purpose of MHE is to estimate states and parameters and to readjust the predicted and measured values of the model. By adjusting the model's parameters and initial conditions, the model prediction matches the previous measurement results. As the estimation range increases, the sensitivity of the solution to x_0 decreases at x_n. The unique d has a significant influence on the current model state in a long enough time range. Therefore, it is not necessary to estimate the initial state x_0 as the degree of freedom in the optimization problem [23], [24].

$$
\begin{aligned}
\min_{\hat{x},\hat{y},\hat{p},\hat{d}} \Phi &= w_m^T (e_U + e_L) + w_p^T (c_U + c_L) + \Delta p^T c_{\Delta p} \\
s.t.\ 0 &= f\left(\frac{d\hat{x}}{dt}, \hat{x}, \hat{y}, \hat{p}, \hat{d}, u\right) \\
0 &= g(\hat{x}, \hat{y}, \hat{p}, \hat{d}, u) \\
0 &\le h(\hat{x}, \hat{y}, \hat{p}, \hat{d}, u) \\
e_U &\ge \hat{y} - y_x + \frac{db}{2} \\
e_L &\ge y_x - \frac{db}{2} - \hat{y} \\
c_U &\ge \hat{y} - \bar{y} \\
c_L &\ge \bar{y} - \hat{y} \\
\Delta p_U &\ge p_i - p_{i-1} \\
\Delta p_L &\ge p_{i-1} - p_i \\
e_U, e_L, c_U, c_L, &\Delta p_U, \Delta p_L \ge 0
\end{aligned} \tag{7}
$$

MHE can use complex dynamic models and processing constraints to prevent estimated parameters from entering unreal areas. MHE can make full use of the continually changing system information and various information to estimate the system state more accurately, not only as a state observer output feedback to MPC but also for system model verification. L1-Norm Moving Horizon Estimation with dead-band, as shown in equation 7.

In the above optimization equation 7, $\hat{x}$, $\hat{p}$ and $\hat{d}$ represent the estimates of x, p and d, respectively; Φ represents minimized objective function result; $\hat{y}$ represents model outputs $\left(\hat{y}_0 \cdots \hat{y}_N\right)^T$; y_x represents measurements $\left(y_{x,0} \cdots y_{x,N}\right)^T$; $\bar{y}$ represents prior model outputs $(\bar{y}_0 \cdots \bar{y}_N)^T$; w_m^T represents measurement deviation penalty; w_p^T represents penalty from the prior solution; Δp_U and Δp_L represent upper and lower parameter change; $c_{\Delta p}$ represents penalty from the prior parameter values; db represents dead-band for noise rejection; Δp^T represents change in parameters; e_U and e_L represent slack variable above and below the measurement dead-band; c_U and c_L represent slack variable above and below a previous model value; N represents the size of the estimation window.

The MHE objective function in equation 7 is implemented in a form suitable for the large-scale model's numerical solution. By using relaxation variables to solve inequality constraints, absolute value functions are avoided. Relaxation variables and inequalities establish a smooth, continuous, and differentiable objective function required by large-scale nonlinear programming (NLP) solver. An essential advantage of L1-Norm MHE is its low sensitivity to data outliers, noise, and measurement drift, which is very important in processing industrial data, leading to instrument drift or failure. Another advantage of L1-Norm MHE is that only linear equations are added to the objective function. Because there is no other nonlinear expression, a numerical solution is usually easier to find the optimal solution.

The MHE structure, as shown in figure 3, at time step k, The nonlinear MHE (NMHE), which is based on a rigorous process model, computes the parameters and states, $\hat{x}$ and $\hat{p}$. The detailed steps are shown below:

1. Initialization step

Given weight matrix w_m^T, w_p^T and Δp^T, initial state x_0, estimated parameter initial value p_0, the dead band db and the size of the estimation window N.

2. MHE step

At a certain time step k, acquire past measurements over a window of size N. When $k < N$, the MHE objective function is a full-information MHE. When $k > N$, the MHE objective function is an approximate MHE.

3. Parameter and state prediction step

Find the best parameter and state trajectory that best fit the considered window of measurements. This is done by minimizing the MHE objective function in equation 7. Repeat the same steps at the next time step.

B. DESIGN OF TRACKING MPC

With control tools like MPC, it is expected that the industrial drying operation will continue to improve its energy efficiency while enhancing product quality and reducing the negative environmental impact of dryers. The dynamic response of the outputs of a system is affected by controlled inputs (or manipulated variables) and uncontrolled inputs (or disturbances). A dynamic model of the system can capture such dynamics. Afterward, the controller can exploit them to make predictions of the system's possible future response as a function of future controlled and uncontrolled inputs. According to a specific performance index, MPC uses these predictions to select the best sequence of future manipulated variables. The best sequence is obtained by solving a numerical optimization problem, which also considers the constraints on input and output variables one must satisfy during the operation of the drum dryer.

The conventional tracking MPC (CMPC) will be compared with the proposed L1-Norm zone MPC design. A common objective function form is the squared error or L2-norm objective (see equation 8). In this form, there is a squared penalty for deviation from a set point or desired trajectory. The squared error objective is simple to implement, has a relatively intuitive solution, and is well suited for Quadratic Programming (QP) or Nonlinear Programming (NLP) solvers.

$$\begin{aligned} \min_{u} \Phi &= \left(\hat{y}-y_t\right)^T W_t \left(\hat{y}-y_t\right) + \hat{y}^T w_y + u^T w_u \\ &\quad + \Delta u^T W_{\Delta u} \Delta u \\ s.t.\ 0 &= f\left(\frac{d\hat{x}}{dt}, \hat{x}, \hat{y}, \hat{p}, \hat{d}, u\right) \\ 0 &= g(\hat{x}, \hat{y}, \hat{p}, \hat{d}, u) \\ 0 &\leq h(\hat{x}, \hat{y}, \hat{p}, \hat{d}, u) \\ \tau_c \frac{dy_t}{dt} &+ y_t = sp \end{aligned} \tag{8}$$

In the above optimization, $\hat{x}$, $\hat{y}$, $\hat{p}$ and $\hat{d}$ represent the state and parameter estimate from L1-Norm MHE. Φ represents minimized objective function result; y_t represents desired trajectory target; W_t represents penalty outside reference trajectory; w_u and w_y represent the weight on input and output; Δu represents manipulated variable change; $W_{\Delta u}$ represents manioulated variable movement penalty; sp represents setpoint; τ_c represents time constant of desired controlled variable response.

IV. PROPOSED L1-NORM ZONE MPC AND NMPC STABILITY

A. DESIGN OF L1-NORM MPC WITH DEAD BAND ZONE TRACKING

From the second part of the system modeling, it can be seen that the cut tobacco drying system is a non-square system (the number of input variables is less than the number of output variables), and there is a problem of lack of freedom in control. For a given setpoint control, the traditional MPC control will appear static error at the output variables, and the control can not achieve satisfactory results. In the cut tobacco drying system, the most critical control task is the cut tobacco's outlet moisture content w. The set values of other output variables do not need to be strictly controlled to a certain value. The control requirements are relaxed to make them stable within the given operation constraints. Thus, the system's freedom degree is increased to a certain extent; the control requirements of the system's critical output variables are met, and the static error of the output variable is eliminated. The L1-Norm zone control's essence is: for the control of the system with a degree of freedom $D < 0$, the zone control strategy is adopted for some outputs, that is, to give up the setpoint of this part of the output. That is, to reduce the number of steady-state equations, to obtain unique solutions, or even infinite solutions (the number of solutions is related to the number of relaxed outputs of the zone control strategy), to eliminate the steady-state residual error of the output (see equation 9). A unique feature of the L1-norm zone MPC is that a dead band zone or no penalty zone is added to the measured value without causing any loss. Only when the model prediction exceeds this dead band zone will the optimizer change the model's parameters. This setting reduces the controller actions to a certain extent, achieving cost savings, and optimizing economic goals.

$$\begin{aligned} \min_{u} \Phi &= w_{hi}^T e_{hi} + w_{lo}^T e_{lo} + \hat{y}^T w_y + u^T w_u \\ &\quad + w_{\Delta u}^T \left(\Delta u_U + \Delta u_L\right) \\ s.t.\ 0 &= f\left(\frac{d\hat{x}}{dt}, \hat{x}, \hat{y}, \hat{p}, \hat{d}, u\right) \\ 0 &= g(\hat{x}, \hat{y}, \hat{p}, \hat{d}, u) \\ 0 &\leq h(\hat{x}, \hat{y}, \hat{p}, \hat{d}, u) \\ \tau_c \frac{dy_{t,hi}}{dt} &+ y_{t,hi} = sp_{hi} \\ \tau_c \frac{dy_{t,l0}}{dt} &+ y_{t,lo} = sp_{lo} \\ e_{hi} &\geq \hat{y} - y_{t,hi} \\ e_{l_0} &\geq y_{t,lo} - \hat{y} \\ \Delta u_U &\geq u_i - u_{i-1} \\ \Delta u_L &\geq u_{i-1} - u_i \\ e_{hi}, e_{l_0}, &\Delta u_U, \Delta u_L \geq 0 \end{aligned} \tag{9}$$

In the above optimization, $\hat{x}$, $\hat{y}$, $\hat{p}$ and $\hat{d}$ represent the state and parameter estimate from L1-Norm MHE. Φ represents minimized objective function result; w_{hi}^T and w_{lo}^T represent penalty outside reference trajectory; e_{hi} and e_{lo} represent upper and lower error outside dead-band; w_u and w_y represent the weight on input and output; $w_{\Delta u}^T$ represents manioulated variable movement penalty; Δu_U and Δu_L represent upper and lower manipulated variable change; sp_{hi} and sp_{lo} represent upper and lower bounds to final setpoint dead-band, if the upper bound of the output region is equal to the lower bound, the problem is simplified to the traditional setpoint tracking problem; $y_{t,hi}$ and $y_{t,lo}$ represent upper and lower bounds to desired trajectory target.

The L1-Norm zone control strategy is applied in systems where the control output's precise setpoint is not important, as long as they are kept within the specified operational constraints. Considering the optimization problem of equation 9, we must consider adding terminal constraints to prevent the cost function from becoming unbounded. These terminal constraints are contained in g and f, which means that the input and output errors are zero in the control time domain. Because the input increment constraint may lead to the optimization problem's infeasibility, L1-Norm zone MPC makes the optimization problem always feasible by adding relaxed variables (all inequality constraints are transformed into equality constraints by adding relaxed variables). When the system state is measurable or estimable, as long as the state estimator converges to the real state of the system in a short time, the controller generated by the solution of the optimization problem will stabilize the closed-loop system.

Literature theorem [25], [26]: for the system with a stable model, it is controllable at the equilibrium point corresponding to the expected input target and output zone. If problem 9 is feasible at k time, then it is feasible at any time step after it. Similarly, if the weight w is large enough, then the control sequence obtained from the solution of problem 9 in a continuous-time step will drive the output of the closed-loop system to a point in the corresponding zone.

Here we explain how the zone control eliminates the system residual error by linearizing the nonlinear system. The linearization relationship between system input variables and output variables is shown in equation 10:

$$G \times U = Y$$
$$G = \begin{bmatrix} * & * \\ * & * \\ * & * \\ * & * \end{bmatrix}_{4\times 2}, \quad U = \begin{bmatrix} T_{c1} \\ T_{c2} \end{bmatrix}_{2\times 1}, \ Y = \begin{bmatrix} w \\ T_{dryer} \\ T_{pout} \\ T_1 \end{bmatrix} \tag{10}$$

G is the system linearized steady-state gain matrix, U is the input variable matrix, and Y is the output variable matrix. G is a non rank matrix, so its column space $c(G)$ is a two-dimensional subspace of R^4. If the matrix Y does not belong to the column space $c(G)$ of G, that is, the matrix Y cannot be expressed linearly by the column vector of G, then the system of equations has no solution, that is, the system has residual error control. The methods to solve this problem are as follows: (1) make the matrix Y belong to the column space $c(G)$ of G, and realize unbiased control. (2) By relaxing some output variables of matrix Y, the degree of freedom of equations is improved, and the unbiased control is realized. The L1-Norm zone MPC (L1-ZMPC) proposed in this article is to use the second method to drive the output target to the target value.

B. FINITE HORIZON NMPC SCHEMES WITH GUARANTEED STABILITY

The specifications for NMPC control functions and dynamic performance are essentially provided through cost functions and constraints. We will not detail the actual tuning tradeoffs and the types of physical and operational constraints, but note that you can usually choose a cost function of type L2-Norm or L1-Norm.

$$\begin{aligned} \Phi &= \left\|\hat{y} - y_t\right\|_{W_t}^2 + \|\Delta u\|_{W_{\Delta u}}^2 + \hat{y}^T w_y + u^T w_u \\ \Phi &= \left\|w_{hi}^T e_{hi}\right\|_1 + \left\|w_{lo}^T e_{lo}\right\|_1 + w_{\Delta u}\left(\Delta u_U + \Delta u_L\right) \\ &\quad + \hat{y}^T w_y + u^T w_u \end{aligned} \tag{11}$$

Different possibilities for achieving closed-loop stability of NMPC using a finite horizontal length have been proposed, see example [14], [27]–[29]. Most of these methods modify the NMPC settings so that the closed-loop stability can be guaranteed independently of the process and performance specifications. This is usually achieved by adding appropriate equality or inequality constraints and appropriate additional penalty terms to the cost function. These additional constraints are usually not driven by physical or expected performance requirements, but their only purpose is to enhance the closed-loop stability. Therefore, they are often called stability constraints [29].

According to the optimality principle of dynamic programming, infinite horizon cost is stable. Theoretically, this leads to an infinite-dimensional problem (except for simple, special cases), so a more practical method is to use a quasi-infinite horizon NMPC to approximate the infinite horizon cost. The following principles are usually helpful to ensure the stability of NMPC [29], [30]:

(1) Sufficiently long horizon N_p to cover most of the dynamic of the process.

(2) A terminal penalty term $F(x(N_p))$ which is added to the cost functional:

$$F(x(N_p)) = \hat{y}^T w_y + u^T w_u \tag{12}$$

(3) The terminal set constraint of type $y(N_p) \in \Omega$ ensures that the state is adjusted to the "close enough" setpoint, so that a feasible and stable controller is known prior to N_p, which ensures that $y(N_p)$ will never leave Ω and eventually approach the setpoint.

(4) Terminal equality constraints of the type $y(N_p) = setpoint$, [14], [31], that ensures convergence in finite horizon. One disadvantage of a terminal equality constraint is that the system must be brought to the setpoint in finite time.

In the quasi-infinite layer NMPC method, a terminal penalty term $F(x(N_p))$ of equation 12 and a terminal region constraint contained in inequality constraint $h(\hat{x}, \hat{y}, \hat{p}, \hat{d}, u)$ are added to the standard setup. On the contrary, the terminal penalty term $F(x(N_p))$ and the terminal region are determined offline, so the cost functional with the terminal penalty term $F(x(N_p))$ gives the upper approximation of the infinite layer cost functional with the stage cost Φ, thus solving the closed-loop performance problem on the infinite layer. In addition, as shown in [14], [27], [28], [30], the stability is realized, and only one optimization problem on the finite layer needs to be solved.

The MPC structure, as shown in figure 3, at time step k, it is assumed that the control stage corresponding to the NMPC is dedicated to guiding the outputs to the specified zones while keeping the manipulated inputs within specified constraints zones. The detailed steps are shown below:

1. Initialization step

Given weight matrix W_t, $W_{\Delta u}$, w_y, w_u, w_{hi}^T, w_{lo}^T and $w_{\Delta u}$, the upper and lower bounds to desired trajectory target $y_{t,hi}$ and $y_{t,lo}$ and the size of the prediction window N_p.

2. NMPC step

At a certain time step k, acquire measure the state $\hat{x}$ and parameter $\hat{p}$. Based on $\hat{x}$, compute the (optimal) sequence of controls over a prediction horizon N_p:

$$u^*(\hat{x}) := \left(u^*(k), u^*(k+1), \cdots, u^*(k+N_p-1)\right)$$

3. Implementation step

Apply the control $u^*(k)$ on the sampling period $[k, k+1]$. Repeat the same steps at the next decision instant.

V. SIMULATION RESULT

This section applies the proposed L1-Norm zone MPC (L1-ZMPC) to the cut tobacco drum dryer system and compares its performance with the conventional tracking MPC (CMPC). The optimization problems (MHE, L2-Norm MPC, and L1-Norm zone MPC) are solved using IPOPT in Matlab based on APMonitor [15].

A. SYSTEM PARAMETERS AND CONSTRAINTS

For the cut tobacco drum dryer system in equation 6, model parameters used in the simulations are given in Table 1. The lower and upper limits of the manipulated inputs are $u_{min} = \begin{bmatrix} 0 & 0 \end{bmatrix}^T$ and $u_{max} = \begin{bmatrix} 200 & 200 \end{bmatrix}^T$, respectively. The lower and upper limits of the changing rates of the two manipulated inputs are $\Delta u_{min} = \begin{bmatrix} 10 & 10 \end{bmatrix}^T$ and $\Delta u_{max} = \begin{bmatrix} 100 & 100 \end{bmatrix}^T$, respectively. The lower and upper limits of system states are $x_{min} = \begin{bmatrix} 0 & 0 & 0 & 0 \end{bmatrix}^T$ and $x_{max} = \begin{bmatrix} 0.2 & 160 & 60 & 120 \end{bmatrix}^T$, respectively. The lower and upper limits of the four system outputs are $y_{min} = \begin{bmatrix} 0.135 & 150 & 20 & 100 \end{bmatrix}^T$ and $y_{max} = \begin{bmatrix} 0.145 & 160 & 60 & 110 \end{bmatrix}^T$, respectively. The lower and upper limits of the three system parameters are $p_{min} = \begin{bmatrix} 0 & 0 & 0 \end{bmatrix}^T$ and $p_{max} = \begin{bmatrix} 200 & 50 & 1000 \end{bmatrix}^T$, respectively.

B. SYSTEM PARAMETERS AND STATES ESTIMATION USING MHE

First, the state and parameter estimation performance of the MHE scheme introduced in Section 3 is illustrated. It is assumed that the three outputs (T_{dryer}, T_{pout} and T_1) are measured every $\Delta T = 1s$ and the measurements are immediately available to the state estimator. First of all, the estimator must predict the outlet moisture content of cut tobacco w, because there is no direct measurement of this output variable. Secondly, three thermal conductivity $keff$, $keff1$ and $keff2$ need to be predicted. We consider that the system is at initially a zero state x_0 and the corresponding initially input is $u_0 = \begin{bmatrix} 100 & 130 \end{bmatrix}^T$. Here, $db = 0.1$ represents dead-band for noise rejection. The choice of MHE window length N is based on extensive simulation. The simulation results show that when N is greater than 6, the estimation performance is not significantly improved. Therefore, N is chosen as 10. In order to illustrate the estimation performance of L1-Norm MHE, a set of step input signals ($u(1:19) = \begin{bmatrix} 100 & 130 \end{bmatrix}^T$ and $u(20:90) = \begin{bmatrix} 130 & 150 \end{bmatrix}^T$) are applied to the nonlinear cut tobacco drum dryer system. Figure 4 shows the results of L1-Norm parameters and states estimation. For this application, the results indicate that L1-Norm MHE provides accurate estimates of three thermal conductivity and four states, especially when the tobacco outlet's moisture content is not measurable; it is also estimated accurately.

C. RESULTS OF LOAD-TRACKING CAPABILITY TESTS

For the cut tobacco drum dryer system, generating the required moisture content of cut tobacco within the required time in response to tobacco production is always the top priority. Therefore, this section first verifies the tracking capability of the proposed L1-Norm zone MPC (L1-ZMPC) and conventional tracking MPC (CMPC) and considers the controller's economic performance in the load-tracking capability test. The nonlinear open equation form model in equation 6 is used in the simulations.

For the conventional tracking MPC (CMPC), we use the equation 8. The sampling time is $\Delta T = 1s$, the prediction horizon is $N_p = 80s$ to cover most of the dynamics of process. $y_t = \begin{bmatrix} 0.14 & 160 & 60 & 110 \end{bmatrix}$ represents the desired trajectory target, here we choose to set points for fixed values. The weighting matrices $W_t = diag\left(\begin{bmatrix} 30 & 20 & 20 & 10 \end{bmatrix}\right)$ represents penalty outside reference trajectory. Because the outlet temperature of cut tobacco is controlled loosely, that is, the corresponding weight coefficient is smaller than the weight coefficient of other output variables. w_u and w_y represent the weight on input and output, here we choose as the identity matrix. $W_{\Delta u}$ represents manipulated variable movement penalty, here we choose as $W_{\Delta u} = diag\left(\begin{bmatrix} 200 & 200 \end{bmatrix}\right)$.

For the proposed L1-Norm MPC (L1-ZMPC), the prediction horizon N_p and the sampling time ΔT are selected to be the same as the conventional tracking MPC (CMPC). w_{hi}^T and w_{lo}^T represent penalty outside reference trajectory, here we choose as: $w_{hi}^T = \begin{bmatrix} 30 & 20 & 20 & 10 \end{bmatrix}$, $w_{lo}^T = \begin{bmatrix} 30 & 20 & 20 & 10 \end{bmatrix}$.

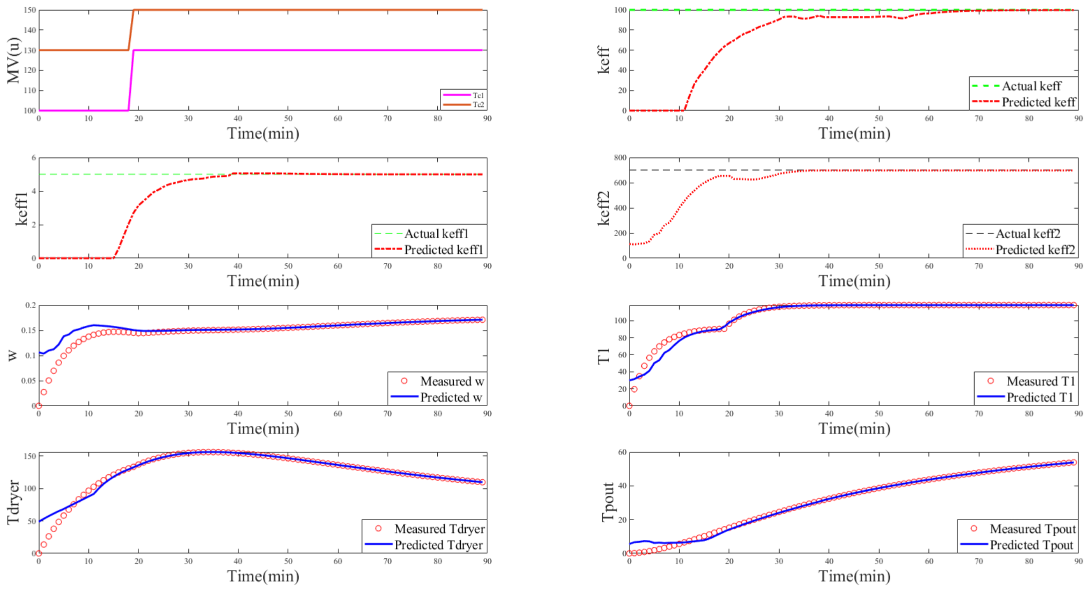

FIGURE 4. Trajectories of the actual states and parameters, and states and parameters estimate by the L1-Norm MHE.

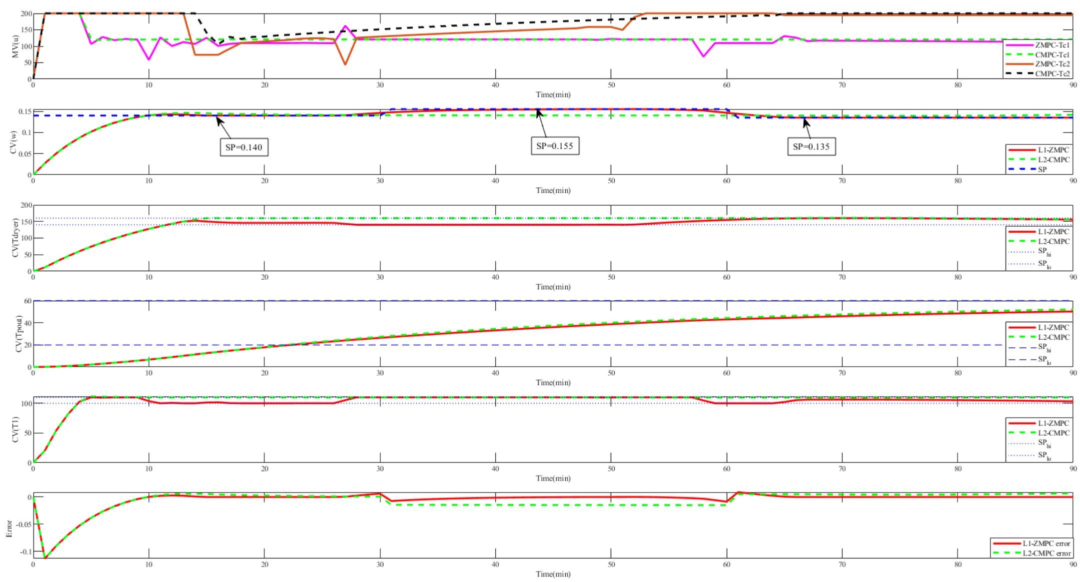

FIGURE 5. Under the nominal condition, L1-ZMPC and CMPC track the change of the cut tobacco outlet moisture setpoint in closed-loop simulation.

w_u and w_y choose as the identity matrix. $W_{\Delta u}$ is selected to be the same as the conventional tracking MPC (CMPC). In the cut tobacco drying process, the primary task is to meet the outlet moisture content of cut tobacco. Under the condition of reducing the operation cost, as long as the cut tobacco outlet temperature, drum dryer temperature and hot air temperature meet the process requirements, energy consumption can be saved. We set a dead band zone for drum dryer temperature T_{dryer}, outlet temperature of cut tobacco T_{pout} and hot air temperature T_1 to meet the process requirements and the outlet moisture content setpoint is same as conventional tracking MPC (CMPC). sp_{hi} and sp_{lo} represent upper and lower bounds to final set-point dead-band zone, here we choose as: $sp_{hi} = \begin{bmatrix} 0.14 & 160 & 60 & 110 \end{bmatrix}$, $sp_{lo} = \begin{bmatrix} 0.14 & 150 & 20 & 100 \end{bmatrix}$.

Simulation is carried out in two typical cases, the first of which is system simulation in a nominal case. Figure 5 shows the controlled variables, the manipulated variables and outlet moisture error of cut tobacco $SP - w$. A set of cut tobacco outlet moisture setpoints ($sp(0:30) = 0.14$,

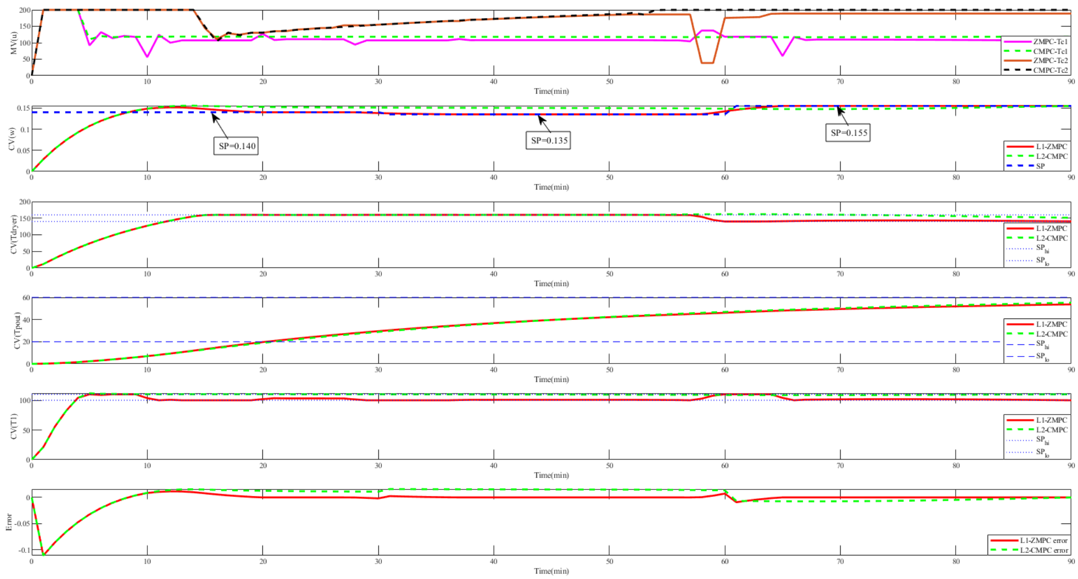

FIGURE 6. Under the disturbance condition, L1-ZMPC and CMPC track the change of the cut tobacco outlet moisture setpoint in closed-loop simulation.

$sp(31 : 60) = 0.155$ and $sp(61 : 90) = 0.135$) are applied to the system. It can be seen that L1-Norm MPC (L1-ZMPC) tracks the cut tobacco outlet moisture setpoint without any offset. CMPC could not track the highest priority cut tobacco outlet moisture setpoint of the system. The other three output control, L1-ZMPC and CMPC can be well controlled in the process range. Comparing the two control algorithms' controller actions, we can see that L1-ZMPC has smaller controller actions. Smaller controller actions mean lower operating costs; that is, energy consumption can be saved.

In the second case, we consider a disturbance in the system, either from upstream equipment or the equipment itself. Here, we assume that the moisture and temperature at the inlet of the cut tobacco from the upstream equipment fluctuate, i.e. $w_{in} = 0.20$, $T_{pin} = 35$; the air temperature at the inlet of the heater changes twice as much, i.e. $T_{in} = 40$. Thereby we can verify the achieved performance of the L1-ZMPC to the CMPC controller. In the modeling part, it has been shown that the system has no direct controller action for the outlet moisture content of the cut tobacco. It is indirectly controlled by drum dryer temperature and hot air temperature, which belongs to a weak control. It can be seen from figure 6 shows the controlled variables, the manipulated variables and outlet moisture error of cut tobacco $SP - w$. The simulation reveals that the CMPC control is a residual control because the cut tobacco's outlet moisture content w exceeds the process setting range of ± 0.005, and the other three output variables conform to the process setting range. The four output variables controlled by L1-ZMPC are all in the process setting range. This simulation demonstrates how well the L1-ZMPC can eliminate some errors in the system model and shows the robustness of the L1-ZMPC to face harsh disturbances that commonly exist in industrial dryers.

From the simulation, we can see that compared with conventional tracking MPC (CMPC), the proposed L1-Norm zone MPC (L1-ZMPC) shows better tracking performance and realizes the controller's minimum action economic characteristics. When the system has disturbances, L1-Norm MPC (L1-ZMPC) shows robust anti-jamming characteristics, especially for weak control (The number of manipulated variables is less than the number of controlled variables).

VI. CONCLUSION

In this article, a novel L1-Norm zone MPC (L1-ZMPC) with dead band zone tracking is proposed for the cut tobacco drum dryer system to account for system economics during the transients while always prioritizing outlet moisture content of cut tobacco tracking. Extensive simulations were carried out to compare the proposed L1-Norm MPC (L1-ZMPC) with a conventional tracking MPC (CMPC). From the simulations, we see that the proposed L1-Norm MPC (L1-ZMPC) has a better tracking capacity than the conventional tracking MPC (CMPC). However, due to the dead band zone tracking targets, the proposed L1-Norm MPC (L1-ZMPC) provides a flexible framework. The proposed L1-Norm MPC (L1-ZMPC) provides a dead band zone to reject the measurement error and stabilize the parameter estimation. It can be used to obtain more economic benefits by tuning the size of the tracking zone. Further, when the system is disturbed and parameter perturbed, the proposed L1-Norm MPC (L1-ZMPC) can use the dead band zone to reject the disturbance and unreasonable parameter perturbations, significantly improving the economic benefits, especially in the case of weak control. Overall, the proposed L1-Norm MPC (L1-ZMPC) with dead band zone tracking provides an attractive control alternative to the conventional tracking MPC (CMPC).

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY

The data used to support the findings of this study are available from the corresponding author upon request.

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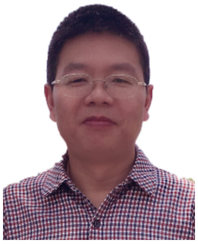

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