Clustering Multi-model Predictive Control for Solar Thermal Power Generation System

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Abstract: There are multi-mode information such as randomness and uncertainty in the solar thermal power generation set thermal process. In this paper, aiming at this problem, clustering multi-model predictive control algorithm is applied to its control. Firstly, the fuzzy clustering is used to measure the data, and then forgetting factor recursive the least square method is used to establish the model of the system. Secondly, the measured collector entrance temperature and solar radiation is considered as disturbance signal, the collector thermal oil flow is used to control outlet temperature and model predictive controller is designed. Finally, the controller was applied to the linear Fresnel thermal generation system to make simulation verification, and results were compared with the single model predictive control, which show that multi-model control precision was higher.

Keywords: Solar thermal power generation, MMPC, Multi-variable forecasting model, Linear Fresnel

1 Introduction

The linear Fresnel solar thermal power generation system has received wide attention because of its simple structure, low cost and good wind resistance[1].The control of outlet temperature steady changes of collector subsystem of solar thermal power generation system is guarantee of generating capacity of solar thermal power generation system. The solar collector system uses the solar radiation to heat the heat conduction oil continuously, regulates the flow of heat conduction oil, and controls the temperature of the outlet heat conduction oil in a certain range, in order to ensure the stability of the power generation.

In recent years, many kinds of intelligent control algorithms are applied to the control of solar thermal power generation system[2]. The model predictive control algorithm is applied in the literature[3-6], but the single model predict control(SMPC) is used. The control objective of the collection system is that the future of the actual output is as close as possible to the future expectations of the target output. In the literature[7-9], the multi-model of linear Fresnel collector subsystem was established, multiple model predictive control (MMPC) was used to reduce the error of the system tracking setting, and clustering multiple model predictive control has been successfully applied to the control of system of which the stochastic is strong.

In this paper, based on the above analysis, the main research contents include:

(1) Collecting 2000 sets of data including the outlet temperature, inlet temperature, solar radiation and heat conduction oil flow to make fuzzy clustering, and DB was selected as the evaluation standard of clustering effect. The data was divided into five categories.
(2) Choose export oil temperature as output, the other three kinds of data as input. Forgetting factor recursive least square method was used to establish a multi-variable forecasting model;
(3) The input oil temperature and solar radiation was considered as disturbance signal, and heat conductive oil flow was considered as control variable. Multi-model predictive switching controller was designed.
(4) The MMPC is applied to the actual linear Fresnel thermal power generation system, which was compared and analyzed with the SMPC results. The MMPC control accuracy is higher than the single model, and the stability of the system control is better.

2 Mathematical model of heat collection system

R Carmona, a Spanish scholar, initially used the mathematical model [1] to describe the heat change of the solar collector [10], and then the model was used to analyze the thermal system [4-6].

$$\rho_f C_f A_f \frac{dT_n(t)}{dt} = \eta_0 G_1 I(t) - \rho_f C_f v(t) \frac{T_n(t) - T_{n-1}(t)}{\Delta x}, n = 1...N \tag{1}$$

where, t is time, s; Δx is collector tube section, m; ρ_f is refrigerant density,kg/m^3; C_f is specific heat capacity,J/(kg·℃); A_f is cross section area of pipe, m; $v(t)$ is conduction heat oil flow, m^3/s; $I(t)$ is solar intensity, W/m^2; η_0 is mirror optical efficiency; G_1 is the optical aperture of reflector, m; T_n is conduction heat oil temperature of oil pipeline outlet, ℃; T_{n-1} is conduction heat oil temperature of oil pipeline outlet, ℃;

Take Δx=L, then (1) can be

$$\rho_f C_f A_f \frac{dT_n(t)}{dt} = \eta_0 G_1 I(t) - \rho_f C_f v(t) \frac{T_n(t) - T_0(t)}{L}, \quad n = 1...N \tag{2}$$

Where, L is the total length of pipeline of the collection system, m; $T_0(t)$ is the input conduction heat oil temperature of collector. The formula (3) can be obtained by discretization (2)

$$T_{out}(k+1) = A_1 T_{out}(k) + A_2 T_{in}(k) + A_3 v(k) + A_4 I(k) \tag{3}$$

Where, T_{out} is outlet temperature, T_{in} is inlet temperature; $v(k)$ is flow of conduction heat oil, $I(k)$ is solar radiation intensity, A_1, A_2, A_3, A_4 is parameters related to system.

3 Clustering modeling of solar thermal power generation set

3.1 Fuzzy clustering of data set

Collecting the data of linear Fresnel thermal power generation system in a region of western China which have been put into power generation to make fuzzy clustering analysis. Fuzzy clustering algorithm is a kind of "soft method" which will gather data together. Fuzzy C means clustering algorithm is used to determine the membership degree of each element to a certain extent, a set of data is divided into C fuzzy class to make the fuzzy objective function is minimum.

The measured data are classified by using the method of subtractive clustering. The algorithm of the forgetting factor least squares identification method is used to generate the multi-model, the process of the algorithm is as follows[11]:

Step1: Determine the number of categories C, fuzzy weight index m and the initial clustering center v;

Step2: The fuzzy membership degree u_{ij} is calculated according to the formula (4).

$$u_{ij} = \begin{cases} \left[\sum_{k=1}^{c} \frac{\|x_i - \upsilon_j\|^{\frac{2}{m-1}}}{\|x_i - \upsilon_k\|^{\frac{2}{m-1}}} \right]^{-1} & \|x_i - \upsilon_k\| \neq 0 \\ 1 & \|x_i - \upsilon_k\| = 0, k = j \\ 0 & \|x_i - \upsilon_k\| = 0, k \neq j \end{cases} \quad (4)$$

u_{ij} is the fuzzy membership degree of category J of Individual. υ_j is cluster center of category J.

Step3: Use formula (5) to calculate the center of each category.

$$\upsilon_j = \frac{\sum_{i=1}^{n} u_{ij}^m x_i}{\sum_{i=1}^{n} u_{ij}^m} \quad (5)$$

Step4: The target value is calculated according to the formula (6) to determine whether the values meet the target value or not. If the values meet the target value, the clustering is end. Otherwise, return **Step2**.

$$J = \sum_{i=1}^{n} \sum_{j=1}^{c} (u_{ij})^m \|x_i - \upsilon_j\| \quad (6)$$

Clustering validity analysis method has many kinds, and this article use Davies Bould n (DB) index to carry on the pros and cons of the classification.

$$DB = \frac{1}{C} \sum_{i=1}^{C} R_i \quad (7)$$

Where

$$R_i = \max_{\substack{j=1,2,\cdots,n \\ i \neq j}} R_{ij}$$

Then

$$R_{ij} = \frac{s(c_i) + s(c_j)}{d(c_i, c_j)} \quad (8)$$

In the formula, $s(c_i)$ is a measure of the closeness of the class and $d(c_i, c_j)$ represents class distance. A typical measurement of closeness of the class and class distance is:

$$s(c_i) = \frac{1}{|c_i|} \sum_{x \in c_i} \|x - v_i\| \quad (9)$$

$$d(c_i, c_j) = \|v_i - v_j\| \quad (10)$$

The index and the Dunn index consider the effect of clustering from the view of geometric point, and the difference is that the DB index takes the average similarity of the class into account. The smaller the index value, the better the clustering effect. In this paper, for 2000 sets of actual power generation data M (m_1, m_2, m_3, m_4) is classified, among them, m1 is the outlet temperature, m_2 flow, m_3 is the heat transfer oil outlet temperature, and the solar radiation is m_4. Fuzzy clustering was used to analyze. When the number of clusters is equal to 5, DB is the smallest, and table 1 lists the clustering results.

Table 1 clustering results

C	3	4	5	6	7
DB	1.3356	0.7017	0.2123	1.0051	0.7617

3.2 Modeling of least squares

Using the above classification data results considered the inlet oil temperature, solar radiation and flow rate of conduction heat oil as input, and outlet temperature as output. In order to overcome the shortcomings of the least squares that its correction ability is poor, forgetting factor recursive least square method is adopted[12]. The algorithm of parameter identification is as follows:

$$\begin{cases} \hat{\theta}(k) = \hat{\theta}(k-1) + K(k)\left[y(k) - \varphi^T(k)\hat{\theta}(k-1) \right] \\ K(k) = \frac{P(k-1)\varphi(k)}{\lambda + \varphi^T(k)P(k-1)\varphi(k)} \\ P(k) = \frac{1}{\lambda}\left[1 - K(k)\varphi^T(k) \right] P(k-1) \end{cases} \quad (11)$$

Where, $\theta(k)$ are parameters to be identified, $K(k)$ is gain matrix; $\varphi(k)$ is observation matrix; $P(k)$ is covariance matrix; λ is forgetting factor. According to the measured data and the operating characteristics of solar thermal power generation collector subsystem, the CAR model (12) is used to identify the parameters and the classification results of the data are combined to establish five mathematical models.

$$\mathbf{Y}(k+1) = \boldsymbol{\varphi}^T(k)\theta \quad (12)$$

Where

$$\mathbf{Y}(k+1) = [y_1(k+1), y_2(k+1), y_3(k+1), y_4(k+1), y_5(k+1)]^{\mathrm{T}}$$

$$\theta = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} \\ a_{21} & a_{22} & a_{23} & a_{24} & a_{25} \\ a_{31} & a_{32} & a_{33} & a_{34} & a_{35} \\ a_{41} & a_{42} & a_{43} & a_{44} & a_{45} \end{bmatrix}$$

$$\boldsymbol{\varphi}^T(k)=\begin{bmatrix} -y_1(k) & u_1(k) & T_{out1}(k) & I_1(k) \\ -y_2(k) & u_2(k) & T_{out2}(k) & I_2(k) \\ -y_3(k) & u_3(k) & T_{out3}(k) & I_3(k) \\ -y_4(k) & u_4(k) & T_{out4}(k) & I_4(k) \\ -y_5(k) & u_5(k) & T_{out5}(k) & I_5(k) \end{bmatrix}$$

θ positive real vector with zero or sufficiently small initial value, $P(0)=10^5 I$, forgetting factor $\lambda=0.95$. Five mathematical models of the solar collector system are shown as(13).

$$\begin{cases} y_1(k+1)=0.9234y_1(k)+0.3011u_1(k) \\ \quad +0.0372T_{in1}(k)+0.0027I_1(k) \\ y_2(k+1)=0.9904y_2(k)+0.2630u_2(k) \\ \quad +0.0291T_{in2}(k)+0.0038I_2(k) \\ y_3(k+1)=0.9895y_3(k)+0.4668u_3(k) \\ \quad +0.0364T_{in3}(k)+0.0029I_3(k) \\ y_4(k+1)=0.9650y_4(k)+0.3771u_4(k) \\ \quad +0.03149T_{in4}(k)+0.0035I_4(k) \\ y_5(k+1)=0.9550y_5(k)+0.3257u_5(k) \\ \quad +0.0419T_{in5}(k)+0.0036I_5(k) \end{cases} \quad (13)$$

Where, $y_i(k)$ is output oil temperature, $u_i(k)$ is the flow rate of conduction heat oil, $T_{ini}(k)$ is input oil temperature，and $I_i(k)$ is solar radiation. Formula (13) is considered as predictive model of the system.

4 Multi-model switching control

The stability analysis of multi model switching is demonstrated and analyzed in the literature [13][14], so the model switching system is stable.

On the basis of multi-model modeling, the model is used to switch on line. Fig 1 is the solar collector multi-model predictive control system. There are ω sub models $M_1, M_2, \cdots M_\omega$ in the picture. Dynamic characteristics of the running process is Identified based on the input and output data (u, y), and output is respectively $\hat{y}_i (i=1,2,\ldots,\omega)$. y_r is the reference input. The output of the model switching strategy is $y_s (1\le s\le \omega)$. The optimal sub model is used to cut into the closed loop system for rolling optimal predictive control[7][15].

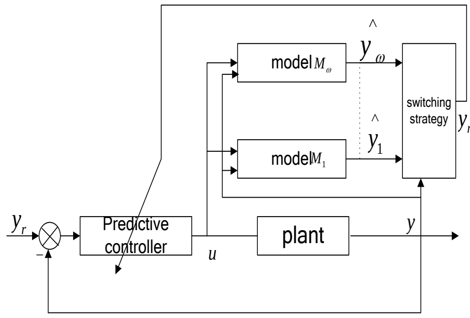

Fig 1 Structure block diagram of the solar collector multi-model predictive control system

At the k moment, $e_i(k)=y(k)-\hat{y}_i(k)$ represents the output error of the actual output and the $i(1<i\le 5)$ sub model. Switching index is:

$$J_i(k)=ae_i^2(k)+b\sum_{j=1}^{l}\rho^j e_i^2(k-j) \qquad (14)$$

The switching condition is that the performance index of the formula (14) is the smallest. The smaller J_i, the smaller the model M_i mismatch. $a>0, b>0$ are respectively the weighted coefficients of the mismatch errors for the present moment and the past l moment. Forgetting factor is $0<\rho\le 1$, which presents the forgetting degree of the mismatch error in the system performance index for the past l moments. l is the time domain length of the past time.

4.1 Predictive controller

Consider the following nonlinear discrete systems[16][17].

$$\begin{aligned} y(k+1)= f\,(y(k),..., \mathrm{y}\left(k-n-1\right), \\ \mathrm{u}\left(k\right),...,\mathrm{u}\left(k-m-1\right)) \end{aligned} \qquad (15)$$

Where, $\mathrm{u}(k)$ and $\mathrm{y}(k)$ are respectively input and output of system, m and n represent the order of the input and output respectively, $f(\bullet)$ is an unknown nonlinear function, and meet the conditions:

1) $f(0,0,\cdots,0)=0$;

2) $f(\bullet)$ is continuous derivative about $y(k),\cdots,y(k-n-1),u(k),\cdots,u(k-m-1)$, and the partial derivative is bounded.

$$\begin{aligned} \left|\partial f(\bullet)/\partial y(k-i)\right| \le k_{\max}, \\ \left|\partial f(\bullet)/\partial u(k-i)\right| \le k_{\max}. \end{aligned} \qquad (16)$$

Theorem: The nonlinear system (16) which meets the condition 1) and 2) can be approximated as follows:

$$\mathrm{A}(z^{-1})y(k) = z^{-d}\mathrm{B}(z^{-1})\Delta u(k) + \mathrm{C}(z^{-1})\xi(k) \quad (17)$$

Where, $y(k)$ and $\Delta u(k)$ are output for the system, control increment $\xi(k)$ is total disturbance signal of system, d is delay time.

$$\begin{cases} \mathrm{A}(z^{-1}) = 1 + \mathrm{a}_{1,1}z^{-1} + \cdots + \mathrm{a}_{1,\mathrm{n_a}} z^{-\mathrm{n_a}} \\ \mathrm{B}(z^{-1}) = \mathrm{b}_{1,0} + \mathrm{b}_{1,1}z^{-1} + \cdots + \mathrm{b}_{1,\mathrm{n_b}} z^{-\mathrm{n_b}},\ l_{1,0} \neq 0 \\ \mathrm{C}(z^{-1}) = 1 + \mathrm{c}_{1,1}z^{-1} + \cdots + \mathrm{c}_{1,\mathrm{n_c}} z^{-\mathrm{n_c}} \end{cases} \quad (18)$$

System prediction output can be represented by (19).

$$\mathbf{Y}^* = \mathbf{Y}_\mathrm{m} + \mathbf{G}\Delta\mathbf{U} \quad (19)$$

The vector in formula (19) can be represented by the following formula.

$$\mathbf{Y}^* = [y^*(k+d \mid k),\ y^*(k+d+1 \mid k), \\ \cdots, y^*(k+N \mid k)]^T \quad (20)$$

$$\mathbf{Y}_\mathrm{m} = [y_\mathrm{m}(k+d), y_\mathrm{m}(k+d-1), \\ \cdots, y_\mathrm{m}(k+N)]^T \quad (21)$$

$$\Delta\mathbf{U} = [\Delta u(k), \Delta u(k+1), \\ \cdots, \Delta u(k+N-d)]^T \quad (22)$$

$$\Delta u(k+i) = u(k+i) - u(k+i-1), \\ i = 0, 1, \cdots, N-d \quad (23)$$

$$\mathbf{G} = \begin{bmatrix} b_{1,0} & 0 & \cdots & 0 \\ b_{2,0} & b_{1,0} & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ b_{N-\mathrm{d}+1,0} & b_{N-\mathrm{d},0} & \cdots & b_{1,0} \end{bmatrix} \quad (24)$$

Where, $\mathbf{Y}_\mathrm{m}$ is the past output for the system, $\mathbf{Y}^*$ is predictive output, and $\boldsymbol{G}$ is the control matrix.

In the formula (21), $y_\mathrm{m}(k+j)$ is determinate by past input and output and expressed by (25).

$$y_\mathrm{m}(k+j) = -\sum_{i=1}^{n_a} \mathrm{a}_{1,\mathrm{i}} y_\mathrm{m}(k+j-i) \\ + \sum_{i=0}^{n_b} \mathrm{b}_{1,\mathrm{i}} \Delta u(k+j-d-i \mid k) \\ + \sum_{i=0}^{n_c} \mathrm{c}_{1,\mathrm{i}} \xi(k+j-i \mid k),\ j = 1, 2, \cdots N \quad (25)$$

Where,

$$\Delta u(k+i \mid k) = \begin{cases} 0, i \geq 0 \\ \Delta u(k+i), i < 0 \end{cases}$$

$$\xi(k+i \mid k) = \begin{cases} 0, i \geq 0 \\ \xi(k+i), i \leq 0 \end{cases}$$

$$y_m(k+i) = y(k+)i, \leq$$

The parameters in the formula (24) can be calculated by (26).

$$b_{\mathrm{j},0} = b_{1,\mathrm{j}-1} - \sum_{i=1}^{j_1} a_{1,\mathrm{i}} b_{\mathrm{j-i},0} \\ j = 2, 3, \cdots, N-d+1 \quad (26)$$

Where,

$$j_1 = \min\{j-1, n_\mathrm{a}\},\quad j-1 > n_\mathrm{b}, b_{1,\mathrm{j}-1} = 0$$

$$\begin{cases} y_\mathrm{r}(k+d-1) = y_\mathrm{m}(k+d-1) \\ y_\mathrm{r}(k+d+i) = \alpha y_\mathrm{r}(k+d+i-1) + (1-\alpha)\omega(k+d) \\ \mathbf{Y}_\mathrm{r} = [y_\mathrm{r}(k+d), y_\mathrm{r}(k+d+1), \cdots y_\mathrm{r}(k+N)]^T \end{cases} \quad (27)$$

$$i = 0, 1, \cdots, N-d$$

$\omega(k)$ is the expected output of k moment, α is diffusion coefficient, and Y_r is reference trajectory vector. Make the objective function (28) the minimum, the optimal control increment (28) can be obtained.

$$J = E\left\{(\mathbf{Y} - \mathbf{Y}_\mathrm{j})^T(\mathbf{Y} - \mathbf{Y}_\mathrm{r}) + \Delta\mathbf{U}^T\boldsymbol{\Gamma}\Delta\mathbf{U}\right\} \quad (28)$$

$$\Delta\mathbf{U} = (\mathbf{G}^T\mathbf{G} + \boldsymbol{\Gamma})^{-1}\mathbf{G}^T(\mathbf{Y}_\mathrm{r} - \mathbf{Y}_\mathrm{m}) \quad (29)$$

The control variable can be represented by formula (30).

$$\Delta u(k) = [1, 0, \cdots 0](\mathbf{G}^T\mathbf{G} + \Gamma)^{-1}\mathbf{G}^T(\mathbf{Y}_\mathrm{r} - \mathbf{Y}_\mathrm{m}) \quad (30)$$

$\boldsymbol{\Gamma}$ is the control weight matrix and unit matrix.

5 Simulation result analysis

Solar thermal power generation system used formula (3) to simulated. Control variable is the flow of conduction heat oil, and input temperature and solar radiation is the measured disturbance signal. According to the disturbance signal to control the size of oil flow, and the outlet temperature follow a predetermined target. Took The parameters of the linear Fresnel power generation demonstration project in the west of china to make simulation analysis. Flow range of conduction heat oil is 3l/s ～ 12l/s. $\rho_f = 800\mathrm{kg/m^3}, \eta_0 = 0.60, C_f = 2600 J\cdot/kg\cdot{}^0C$, T=20 s, L=220m, A_f =0.65m^2, $G = 0.80m$. Single model and multi-model are used to make predictive control respectively. $\rho = 0.7$, α =0.35, the length of control took 1, and control weighting coefficient took 0.9. Simulation results of two algorithms are shown in Fig 2 to Fig 7. Fig 2 and Fig 3 are the actually measured solar radiation intensity and input oil temperature. Fig 4 and Fig 5 are the results of the model predictive control and the tracking error. Fig 6 is the process for multi-model switching. Fig 8 and Fig 7 are the results of multi-model switching control and tracking error.

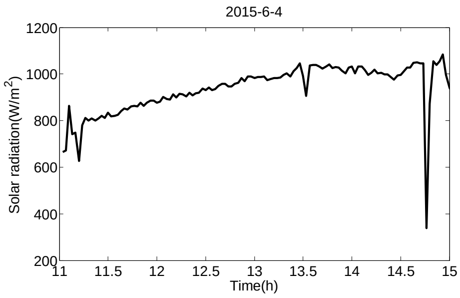

Fig 2 Solar radiation intensity

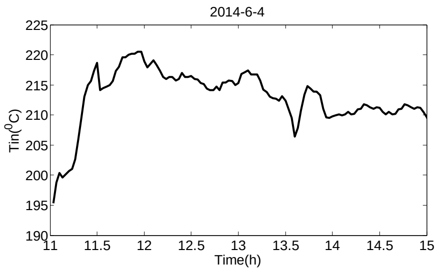

Fig 3 Input oil temperature

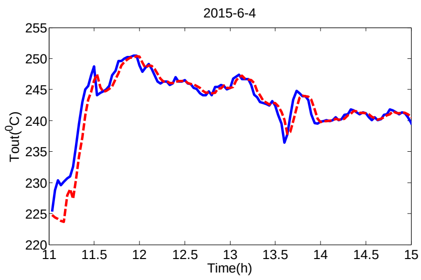

Fig 4 Results of single model predictive control

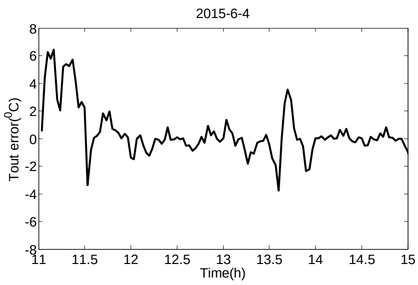

Fig 5 Output oil temperature error of single model predictive control

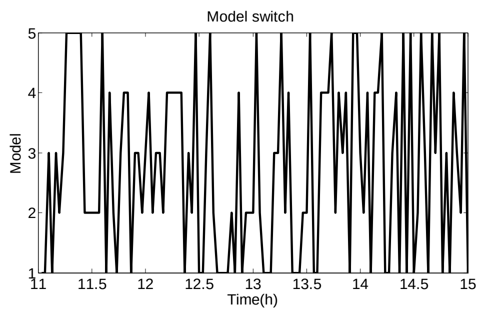

Fig 6 Model selection in control process

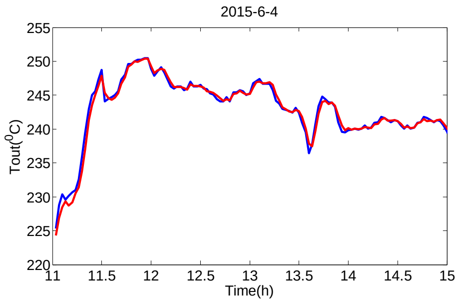

Fig 7 Results of multi-model predictive control

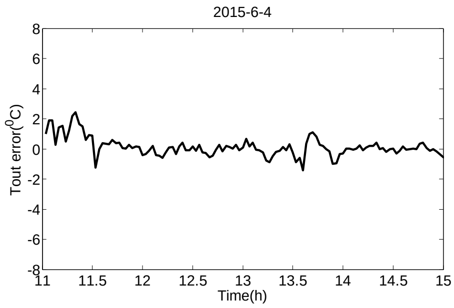

Fig 8 Output oil temperature error of multi-model predictive control

From Fig 5 and Fig 8, it can be seen that the error of multi model control is smaller and the stability of control is better. MSE was calculated through SMPC 1.66886189, and the MSE of multi-model control was 0.65030726.

6 conclusion

In this paper, we collect the data of 2000 sets of solar thermal power generation collect subsystem, classify them, and set up its mathematical model. Predictive controller was designed to make multi-model switching control. The single model and multiple model were applied to the linear Fresnel solar thermal power generation system in Gansu province which has been put into use to make simulation analysis. From Fig 3 and Fig 6, it can be seen that the multi-model switching control precision is higher, and the time lag is shorter. Compared with the single model predictive control, the mean square error of the multi- model is smaller. The results show that the tracking error is reduced and the convergence speed and tracking accuracy of the system are improved by using the multi model predictive control strategy.

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