

The Multi-Objective Robust Optimization of Molding Process Parameters for Particles from Tobacco Stems and Wood Chips

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Abstract: Considering the stochastic uncertainty of three parameters (molding temperature, moisture content of raw materials and molding pressure) in the process of particles from tobacco stems and wood chips, the analytical robust optimal design of two quality properties (particle density and radial resistance pressure) is carried out. Based on the quadratic regression equation between performance and parameters, and the improved analytic hierarchy process (AHP) is used to deal with multi-objective. Taking the minimum variance of performance fluctuation as the objective, the optimal combination of process parameters is obtained by interior-point algorithm. Comparing with deterministic optimization, the variance of particle density is reduced by 8.45%, and the variance of radial resistance pressure is reduced by 29.76%, which has a good reference value to the actual production of biomass fuel.

Keywords: tobacco stems and wood chips; process parameters; robust optimization; multi-objective

INTRODUCTION

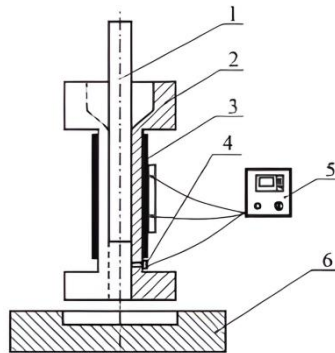
Biomass fuel molding technology is an effective way to achieve the transformation of large-scale renewable energy [1-2], which is mainly to crush some agricultural and forestry crops to a certain particle size, and then to extrude them into dense material fuel by mould. Tobacco stems and wood chips belong to lignocellulosic materials [3-4], which are widely distributed in China. Making them into biomass fuel can not only protect the environment but also enrich energy. Therefore, the research on the molding technology of particles from tobacco stems and wood chips is of great value. In recent years, scholars at home and abroad have carried out some research on the biomass pellet fuel molding technology. Shaw [5] compared the densification of wheat straw and poplar sawdust; Adapa P K [6] analyzed the densification of rape and wheat straw by experiment; Stahl M [7] has studied the quality of wood chips molding under different pressure and temperature; Wang [8] has optimized the molding process of corn straw by response surface method; Zhang [9] has studied the characteristics of water hyacinth fuel molding process and given the primary and secondary infiltration of process parameters; Lin [10] has studied the characterization of tobacco stem biochar and the mechanical property of charcoal moulding fuel; Zhang [11] has studied the forming characteristics of the particles fuel in the bacteria bract, sawdust and tobacco stalk. Rao [12] optimized the molding process parameters and the compound ratio for biomass particles fuel from tobacco stems and wood chips.

The stochastic uncertainty of molding process parameters for compound particles form tobacco stems and wood chips can lead to great fluctuation of quality. At present, there are few reports about the compound tobacco stems. In the compression molding of biomass, the optimal combination of parameters is generally selected by orthogonal test, and the dispersion effect of factors is ignored. If the physicochemical process of biomass components are interfered by various environments, the product quality is difficult to be stable. The robust design proposed by Taguchi [13] is originated from the three stage design of product quality control, which has been accepted and widely used by scholars and engineers from different countries. Without eliminating or reducing the uncertainty factors, the robust design can make full use of the non-linear attribute effect and optimize the level of parameters to minimize the impact of the uncertainty factors on the performance fluctuation, so it can improve the robustness of product quality. This paper avoids all kinds of experimental design and data statistical processing, and according to the mathematical relationship between the quality performance and the main molding process parameters of particles, the analytical robust design principle is used to optimize the level of process parameters.

1. MATHEMATICAL MODEL OF BIOMASS PARTICLES QUALITY PERFORMANCE AND PROCESS PARAMETERS

The molding device of biomass pellet fuel from tobacco stems and wood chips is composed of die, concave die, heating element, temperature sensor, control box and base, etc. (the structure is shown in Figure 1). Its technological process is: drying→crushing→adjusting moisture content→compounding→heating→pressurizing→molding→cooling→quality

measurement. The shaped biomass particles are shown in Figure 2. The main instruments used in performance test are electronic universal testing machine, electronic balance and vernier caliper, etc.



1 Die; 2 Concave die; 3 Heating element; 4 Temperature sensor; 5 control box; 6 Base

Figure 1 Device diagram



Figure 2 Compound biomass molding particles

The reference [12] pointed out that the best mass fraction ratio of the compound components is 1:1. Fixing the compound ratio, the level of the moisture content of raw materials are (12%, 14%, 16%), the level of the molding temperature are (90 °C, 100 °C, 110 °C), the level of the molding pressure are (4.5kN, 6.0kN, 7.5kN), the quality performance are radial resistance pressure (kN) and particle density (kg / m³), the orthogonal experiment of L₉ (3³) is designed, and the quadratic regression equations are obtained by using the response surface method to fit the test data based on the least square principle. Here, I

write the specific mathematical functions are [12]:

$$Y_i = \beta_i + a_{i1}X_1 + a_{i2}X_2 + a_{i3}X_3 + b_{i1}X_1X_2 + b_{i2}X_1X_3 + b_{i3}X_2X_3 + c_{i1}X_1^2 + c_{i2}X_2^2 + c_{i3}X_3^2 \quad (1)$$

Here Y_i is the response value of each quality performance, β_i is the intercept term, a_{ij} is the linear coefficient, b_{ij} is the interaction term coefficient, c_{ij} is the quadratic term coefficient.

Table 1 The coefficients of quadratic regression equations

Coefficients	β_i	a_{i1}	a_{i2}	a_{i3}	b_{i1}	b_{i2}	b_{i3}	c_{i1}	c_{i2}	c_{i3}
Y_1	-6.272	-0.210	0.375	2.454	0.007	0.034	0	-0.019	-0.043	-0.015

Y_2	972.814	-1.212	58.612	684.308	2.573	-7.542	0	-7.178	-0.174	48.755
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The fitting degree of the regression equations (1) are high, there is no interaction between temperature and pressure, the correlation coefficient of Y_1 is $R_1 = 0.889$, the correlation coefficient of Y_2 is $R_2 = 0.875$. According to the absolute value of M-1 of the regression equation, we can judge the influence degree of each process parameter on quality performance. Specifically, the most important factor of radial resistance pressure is molding pressure, the order of molding temperature and moisture content of raw materials is not much different; the factors order of particle density is molding pressure > molding temperature > moisture content of raw materials.

2. ROBUST OPTIMIZATION MODEL OF BIOMASS PARTICLES

Setting the standard deviation of process parameters are $(\sigma_{X_1}, \sigma_{X_2}, \sigma_{X_3})$, and the noise factors are independent to each other. According to the principle of analytical robust design [14], the performance is approximately expanded at the standard value of variables according to first-order Taylor series, so the expectation and variance of performance are:

$$\begin{aligned}\mu_{Y_i} &= Y_i(X_1^*, X_2^*, X_3^*) \\ \sigma_{Y_i}^2 &= \left(\frac{\partial Y_i}{\partial X_1}\right)^2_{X_1^*, X_2^*, X_3^*} \sigma_{X_1}^2 + \left(\frac{\partial Y_i}{\partial X_2}\right)^2_{X_1^*, X_2^*, X_3^*} \sigma_{X_2}^2 + \left(\frac{\partial Y_i}{\partial X_3}\right)^2_{X_1^*, X_2^*, X_3^*} \sigma_{X_3}^2\end{aligned}\quad (2)$$

Considering that the dimensions of quality are inconsistent, it is necessary to unify the performance data, the numerical benchmark of Y_1 and Y_2 are 1.3kN and 1200kg/m³. Then the normalized expectation and variance are:

$$\begin{aligned}\mu'_{Y_1} &= Y_1(X_1^*, X_2^*, X_3^*)/1.3, \quad \mu'_{Y_2} = Y_2(X_1^*, X_2^*, X_3^*)/1200; \\ \sigma'^2_{Y_1} &= \left(\frac{\partial Y_1}{\partial X_1}\right)^2_{X_1^*, X_2^*, X_3^*} / 1.3^2 \sigma_{X_1}^2 + \left(\frac{\partial Y_1}{\partial X_2}\right)^2_{X_1^*, X_2^*, X_3^*} / 1.3^2 \sigma_{X_2}^2 + \left(\frac{\partial Y_1}{\partial X_3}\right)^2_{X_1^*, X_2^*, X_3^*} / 1.3^2 \sigma_{X_3}^2, \\ \sigma'^2_{Y_2} &= \left(\frac{\partial Y_2}{\partial X_1}\right)^2_{X_1^*, X_2^*, X_3^*} / 1200^2 \sigma_{X_1}^2 + \left(\frac{\partial Y_2}{\partial X_2}\right)^2_{X_1^*, X_2^*, X_3^*} / 1200^2 \sigma_{X_2}^2 + \left(\frac{\partial Y_2}{\partial X_3}\right)^2_{X_1^*, X_2^*, X_3^*} / 1200^2 \sigma_{X_3}^2.\end{aligned}\quad (3)$$

In order to transform the multi-objective optimization problem into a single objective optimization model, the improved AHP can be used to evaluate the primary and secondary of multi-objective [15]. We think that the status of particle density and radial resistance pressure are almost the same, so:

$$\begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}\quad (4)$$

The particle density and the radial resistance pressure are bigger, the quality of biomass pellet fuel is better. In order to ensure the robustness of the design, the robust design model based on variance can be established as follows:

$$\begin{aligned}\text{find} \quad & X_1^*, X_2^*, X_3^* \\ \min \quad & \sigma'^2_Y = w_1 \sigma'^2_{Y_1} + w_2 \sigma'^2_{Y_2} \\ \text{st.} \quad & \begin{cases} \max \mu'_{Y_1} \\ \max \mu'_{Y_2} \end{cases}\end{aligned}\quad (5)$$

The (5) is a nonlinear optimization problem with constraints. Considering the special properties of constraints, the (5) can become a multi-objective unconstrained optimization, that is:

$$\begin{aligned}\text{find} \quad & X_1^*, X_2^*, X_3^* \\ \min \quad & Z = \varepsilon_1 \sigma'^2_Y - \varepsilon_2 (w_1 \mu'_{Y_1} + w_2 \mu'_{Y_2})\end{aligned}\quad (6)$$

Here $\varepsilon_1, \varepsilon_2$ are the weight distribution coefficients of goal and constraint.

3. RESULTS AND ANALYSIS OF PROCESS OPTIMIZATION

Due to the noise factors, such as instability of moisture content, ram movement resistance, and temperature control error, so the moisture content, molding temperature and molding pressure are all random variables in the process of biomass molding test. In general, assuming that the control measures of three process parameters are not significantly different, that is their tolerance is 10% of the nominal value and the standard deviation is 1/3 of the tolerance. Meanwhile, the range of moisture content of raw materials is limited to (0.12-0.16), the range of molding temperature is limited to (90 °C-110 °C), and the range of molding pressure is limited to (4.5kN-7.5kN). The weight coefficients of objective and constraint are 0.7 and 0.3. In MATLAB, the fmincon can solve the multidimensional nonlinear optimization with constraints. Its interior point algorithm synthesizes the calculation accuracy and convergence speed. The robust optimization toolbox is shown in Figure 3.

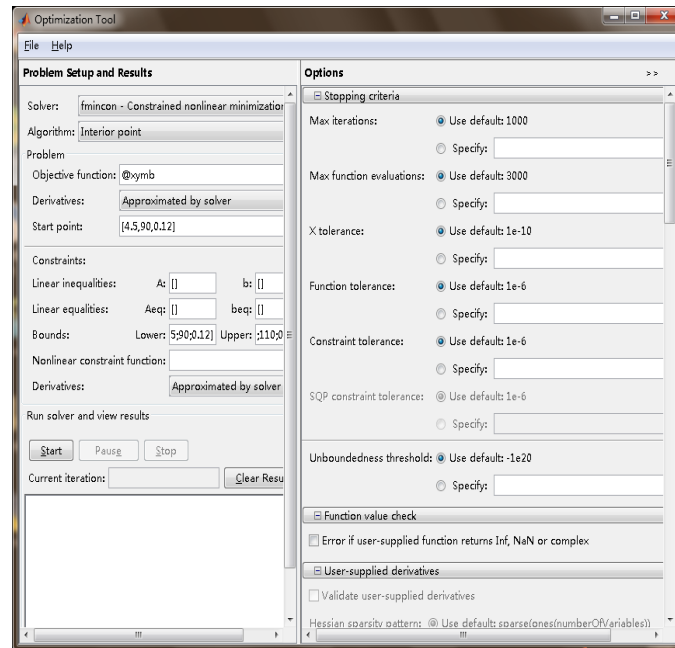


Figure 3 MATLAB Optimization Design Toolbox

The results of robust optimization and deterministic optimization [12] are shown in Table 2.

Table 2 Comparison of optimization results

Design method	X_1^*	X_2^*	X_3^*	Y_1	Y_2	σ_{Y_1}	σ_{Y_2}
Deterministic design	13.5%	101°C	6.5kN	1.73kN	1334.56 kg/m ³	7.8002	87.5264
Robust design	12.0%	90°C	7.0167kN	1.3419kN	1269.36 kg/m ³	5.4783	80.1276

It can be seen from table 2 that the expectation values of Y_1 and Y_2 in robust optimization are reduced compared with deterministic optimization, which indicates that the biomass quality is not fully optimal, but the variance of performance fluctuation is significantly improved. In a sense, the expectation and variance of robust design are mutually restricted.

Similarly, we change the weight coefficients of objective and constraint to 0.3 and 0.7, so the new robust optimization design is:

$$X_1^* = 12\%, X_2^* = 90^\circ\text{C}, X_3^* = 7.0428\text{kN}, Y_1 = 1.3495\text{kN},$$

$$Y_2 = 1270.01 \text{ kg/m}^3, \sigma_{Y_1}^2 = 5.4785, \sigma_{Y_2}^2 = 80.2010. \quad (7)$$

It can be seen that changing the weight coefficients of expectation and variance can change the optimal combination of process parameters. Therefore, the robust design is a technical scheme to ensure the expectation of product performance within a reasonable range and try to make the performance more stable, which is in line with the essence of multi-objective strategy.

In order to verify the effectiveness of the design results, the two sets of robust process parameters are selected for the test, and the measured values of particle density are 1330.82 kg/m^3 and 1333.51 kg/m^3 , the measured values of radial resistance pressure are 1.4089 kN and 1.4170 kN , whose errors are all less than 5% of the calculated values. Therefore, the robust optimization model in this paper has certain reliability.

CONCLUSION

The influence of molding process parameters for particles from tobacco stems and wood chips on the quality performance is not a single trend, but a comprehensive relationship. Considering a variety of random interference factors, the analytical robust design of biomass is carried out by using the response surface method. Comparing with the relevant data of references, the following conclusions are obtained:

(1) When the mixture ratio of tobacco stems and wood chips is 1:1, the density and radial resistance pressure of particles are all quadratic polynomial functions of molding temperature, moisture content of raw materials and molding pressure, and there is no interaction between molding temperature and molding pressure.

(2) The robust optimization of process parameters for particles from tobacco stems and wood chips is: the moisture content of raw material is 12.0%, the molding temperature is 90°C , and the molding pressure is 7.0167 kN . Under this combination, the variance of the radial resistance pressure is 5.4783, and the variance of particle density is 80.1276. Comparing with the deterministic design, the robustness is greatly improved, and the anti-interference ability is enhanced.

(3) The robust optimization design of biomass particles molding quality based on a single objective that is a combination of the variance and expectation of quality. The designer can choose different weight distribution to adjust the robust process parameters.

In the next step, the robust design method can be extended to the more complex advanced quality technology management in molding process of biomass pellet fuel.

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