

# 3d Modeling and Multi-Objective Optimization of Automatic Grain Baling Machine Support

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## Abstract

Based on the multi-objective optimization theory based on response surface, the support of automatic grain baling machine with three columns is optimized to achieve the lightweight target. The 3D model is built by Solid works and the structure of the weak link of the support is optimized by using the response surface optimization module of Ansys Workbench. In the design, the mass, the total shape variable and the equivalent stress of the support are considered synthetically. Under the requirement of ensuring the actual work of the support, the mass of the support decreases by 20.4 kg, which accounts for 0.95% of the mass before the optimization, which saves the material and reduces the cost.

## Keywords

Ansys Workbench; Solid works 3D modeling; Multiobjective optimization; support.

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## 1. Introduction

Automatic grain packing machine, also called quantitative packing machine, is a packaging machine which integrates feeding, weighing, packing, transporting, sewing and packing under the control of computer. Automatic food packaging machine consists of four main parts: automatic weighing equipment, conveying equipment, sewing equipment and computer control equipment. It is urgently needed in the domestic market at present. It is especially important in grain packaging machinery because of its advantages of fast packing speed and high precision. Its optimal design and operation of proficiency directly affect the speed of grain packaging.

The support is the main bearing part of the automatic grain baling machine. In order to provide sufficient strength and rigidity, the larger safety factor is often used in actual production, which results in the increase of the support size and the violation of the lightweight design criterion (Hu et al., 2013). In this paper, the three-column grain baler bracket is taken as the optimization object, and the three-dimensional model of the support set up by Solid works is imported into the ANSYS Workbench software for the static analysis of finite element method. The size of the maximum equivalent stress and the maximum integral variable is set as the optimal input variable, and the maximum stress and the maximum shape variable as well as the mass of the support are taken as the optimal output parameters to optimize the design of the support. The optimal solution of support lightweight is obtained. The three-dimensional model of automatic grain baling machine is shown in figure 1.

## 2. Finite Element Analysis of Support

Method of multi-objective algorithm combined with finite element is adopted in Literature (Lv, Z et al., 2014). The steps of product optimization design with Ansys Workbench are as follows: modeling, adding dimension parameters and material attributes, meshing and adding loads and constraints, defining target parameters and state parameters are compared and verified (Cha and Yang, 2012).

The three-dimensional model of the scaffold was built in Solid works and imported into workbench. Because of the optimization design, the imported model file must be the original model file of Solid works, and must not be imported in the intermediate format, so as to ensure that the two software can realize the function of bidirectional parameter. The model is meshed with triangular shape and 50 mm mesh size. The mesh effect diagram is shown in figure 2, in which there are 42787 nodes and 24509 units.

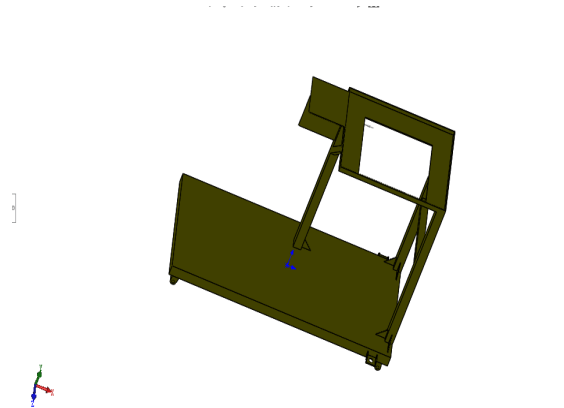


Fig. 1 scaffold model

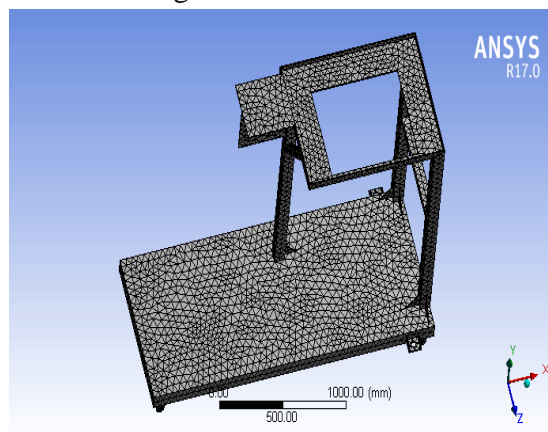


Fig. 2 mesh division diagram

In practice, the support supports weight from food and weighing devices, so it is known that it has four fixed support points and a bearing surface. Add load to the bracket: four pedestals at the bottom of the bracket are subject to a fixed constraint, and the top plane imposes a load of 27000N from the fuselage and grain weight (in the case of a full storage bin).Add the solution to the Solution option as a global variable and equivalent stress, click on the "Solve" software to automatically calculate the result. The deformation cloud diagram and isotherm effect of the optimized support are shown in Fig. 3 and Fig. 4.

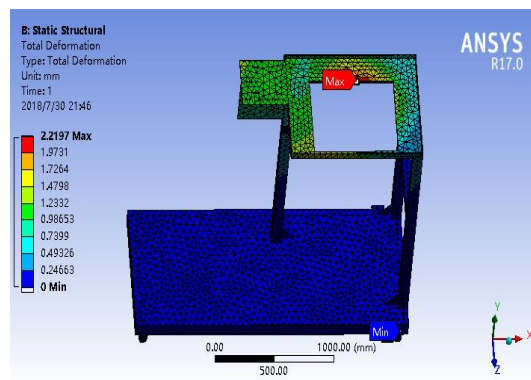


Fig. 3 variable cloud map

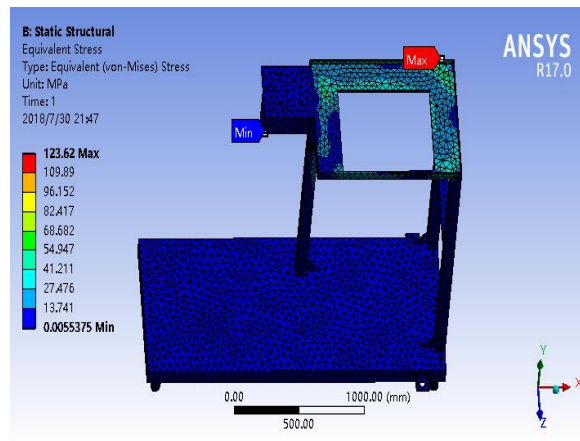


Fig. 4 equivalent stress cloud diagram

From Fig. 3, we can conclude that the maximum total shape variable of the bracket appears at the inner edge of the support surface, which is 2.2197mm.

From Fig. 4, we can find that the maximum equivalent stress of the support appears on the edge of the support surface, which is 123.62 MPa. The material of the support is ordinary carbon structural steel, the elastic modulus is  $E=2.1e+011N/m^2$ , the Poisson's ratio is 0.28, the density is 7800 kg/ m, the tensile strength is 375-500 MPa, the safety factor is 1.3, the allowable stress of the material is 288.46 MPa, which is much larger than the maximum stress of the scaffold.

From the results of finite element analysis, we can get a lot of surplus of material performance, which results in waste of resources, so the scaffold can be optimized to meet the requirements of strength and stiffness to achieve lightweight standards. The model is parameterized by using the cross section size of maximum deformation and maximum stress as input parameters.

### 3. Parameterization of the Model

To optimize the design using Ansys Workbench, we first need to parameterize the model. The so-called model parameterization is to set the dimension related to optimization in the model to the dimension parameter that can be recognized by workbench. This process is done in Solid works. The results of finite element analysis select the dimension of the most dangerous section as the optimal input variable, and add the prefix "DS\_" to it to establish a parameterized model. Directly from the SolidWorks into the Workbench software, size optimization. Figure 5 shows the cross section parameters of the dangerous section.

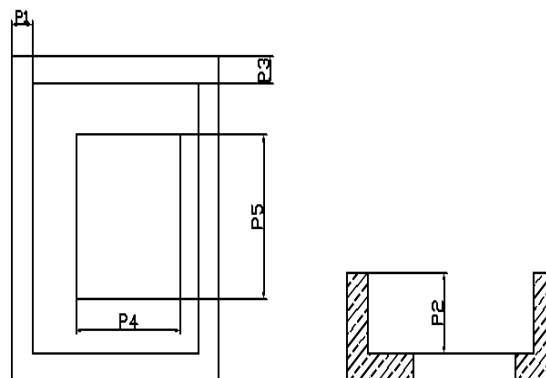


Fig. 5 Section parameters

### 4. Construction of Response Surface Model

The response surface model actually arranges the experimental design table by using the experimental design method, applies the theory of statistics to the process of optimization design, and simulates the function relationship between the various design variables and the performance indexes by

constructing the fitting agent model. In the process of optimization, all the optimization fitness values are actually calculated by the response surface model. In this process, the original optimization of a large number of finite element calculation is replaced, and the calculation time and cost can be guaranteed at the expense of certain precision.

The experimental design table is arranged by CCD (central composite sequential design) with the input parameters of P1, P2, P3, P4, P5, the mass of the support, the maximum total new variable and the maximum equivalent stress as the output parameters. The range of values for each variable is defined. Clicking on the Preview system will automatically generate 25 design points and click Update to generate the calculated results. The range of values for each design variable is shown in Table 1.

Table 1. Range of design variables

project	input parameter /mm				
	P1	P2	P3	P4	P5
initial value	5	35	5	610	710
upper limit value	6	45	6	630	730
lower limit value	4	33	4	590	690

Suppose the functional relationship between design variable X and response surface Y (X) is shown in equation (1).

$$Y(X) = M(X) + \varepsilon = \sum_{i=0}^b a_i \beta_i(X) + \varepsilon \tag{1}$$

M (X) is the approximate function of the optimization objective design variable X and represents the response surface model;  $\varepsilon$  is a comprehensive error, including modeling errors and random errors and so on; B is the number of base functions and  $\beta_i(X)$  is a polynomial function of design variable X. The second order polynomial response surface model is shown in (2) (M.E.,2016).

$$M(X) = a_0 + \sum_{i=1}^n a_i x_i = \sum_{i=1}^n a_{ii} x_i^2 + \sum_{i<j}^n a_{ij} x_i x_j \tag{2}$$

By using the least square method to solve the coefficients of each item in formula (2), the following results can be obtained:

$$A = (a_0, a_1 \dots a_b)^T \tag{3}$$

$$A = (X^T X)^{-1} X^T Y \tag{4}$$

Where X is the base function matrix, and its concrete form is:

$$X = \begin{bmatrix} \beta_1(X_1) & \beta_2(X_1) & \dots & \beta_b(X_1) \\ \beta_1(X_2) & \beta_2(X_2) & \dots & \beta_b(X_2) \\ \dots & \dots & \ddots & \dots \\ \beta_1(X_q) & \beta_2(X_q) & \dots & \beta_b(X_q) \end{bmatrix} \tag{5}$$

When there are too many design variables in the optimization design process, the fitting accuracy of the second-order polynomial response surface model will be reduced, but if the higher order model is used, the calculation is difficult to accept. Therefore, this paper chooses the second-order polynomial approximation to simulate the response surface. Select Response surface, select the type of response surface as complete second-order polynomial, update the data to generate response surface model. By observing 2D or 3D response surface models, we can see the influence of each input parameter on the mass, maximum stress and maximum shape variables of the support. The sensitivity is the influence of the input parameters of the value system on the output results. The

relatively small parameters of the sensitivity can be ignored in order to reduce the number of parameters and reduce the amount of calculation (Xia et al.,2012).If we look at the local sensitivity diagram shown in figure 6, we can see that the variables P2 and P1 (P2 have the highest sensitivity to the result) are the main variables that affect the optimal output variables, while P3P4 and P5 have little effect on the output variables. It is shown that the selection of parameters is not suitable, so the three parameters of P3P4 and P5 are set aside, and P1 and P2 are taken as the optimized input parameters.

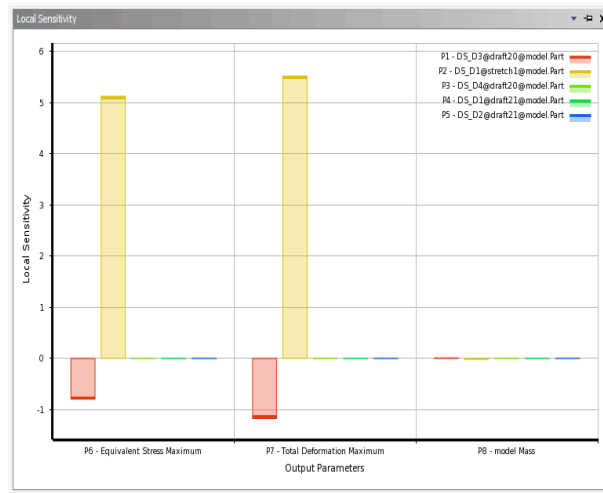


Figure 6 local sensitivity diagrams

The experimental design table is generated, and the calculation results are shown in Table 2

Table 2 optimal design table

Number	P1/mm	P2/mm	Mass/kg	Maximum deformation/mm	Maximum stress /MPa
1	5	39	2127.6	4.1355	142.45
2	4	39	2127.6	4.2586	162.82
3	6	39	2127.6	4.0333	123.85
4	5	33	2151.1	1.7631	107.24
5	5	45	2104.2	60.979	972.21
6	4	33	2151.1	1.8123	128.45
7	6	33	2151.1	1.7259	98.614
8	4	45	2104.2	60.33	975.12
9	6	45	2104.2	61.396	962.14

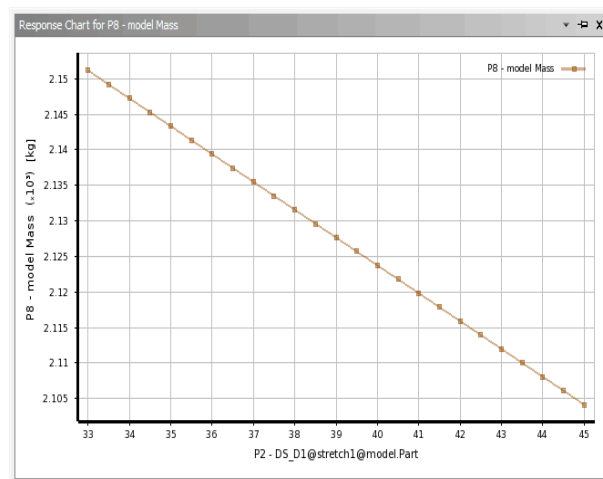


Fig. 8 relationship between P2 and support mass

Next, the influence of P2 on the optimal output parameters is studied. Figure 8 / 9 / 10 shows the relationship between P2 and the support mass, the maximum stress of the support and the maximum shape variable, respectively.

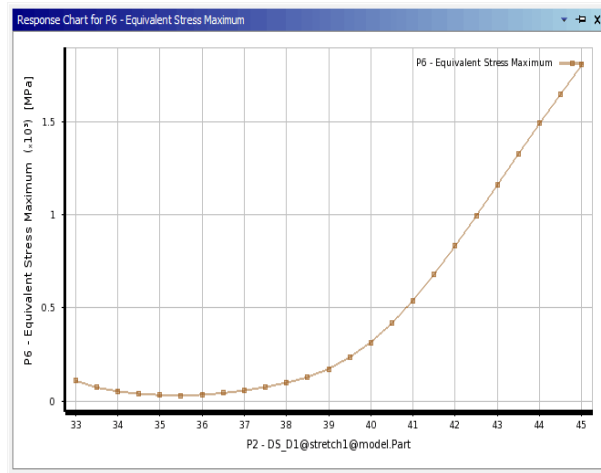


Fig.9 relationship between P2 and maximum stress

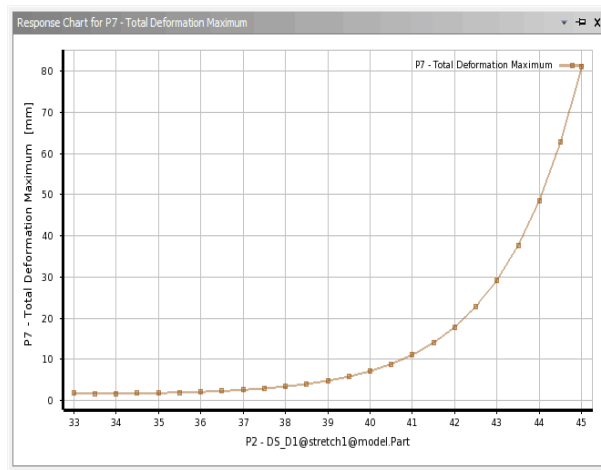


Figure 10 relations between P2 and maximum shape variable

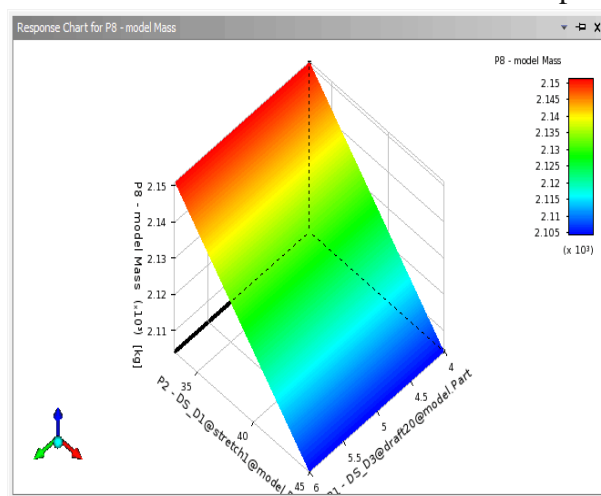


Fig. 11 relationship between P2P1 and support mass

As the input variable P2 increases, the mass of the scaffold decreases, while the maximum shape variable increases. The maximum equivalent stress first decreases, and when the P2 value exceeds 36mm, it presents an increasing trend. The analysis shows that the smaller the mass of the bracket,

the smaller the size of the thin wall at the support surface, and the larger the maximum shape variable, the correlation between the mass and the maximum shape variable.

The first three diagrams are the two dimensional relation diagram of the output result of P2 pair and the 3D relation diagram of the interaction between P1 and P2 on the mass of the scaffold as shown in Fig. 11.

## 5. The Establishment of Mathematical Model

In the field of mechanical engineering design, one of the most important problems is dimensional synthesis of mechanisms in terms of function, motion or path generation categories (Liu et al.,2014).Optimization design is to apply the optimization principle and technology to the design field, and choose the best plan in a variety of design options.Its three elements are: design variables, constraints, and objective functions (Zhang and Wang,2014).In this paper, the objective function is to minimize the total mass and total deformation of the support on the premise of meeting the requirements of strength and stiffness:  $\min M(P)$ ,  $\min D(P)$ .The design variable is the size of the dangerous section. In combination with the object studied in this paper, the two optimized input parameters P1, P2 (see Table 1 for the range of values) are the design variables.According to the content of the research and the actual situation, the state variables are the deformation and stress of the scaffold. That is to say, the constraint condition in the optimization process is to limit the maximum stress of the support within the allowable range of the material, and the maximum stress is not more than 288 MPa. In this paper, the multi-objective function is composed of obvious equations (Jong,2014):

$$\left\{ \begin{array}{l} M(P) = \min M[P1, P2, P3] \\ D(P) = \min D(P1, P2) \\ P = (P1, P2, P3)^T \\ g_i(P) = g_i(P1, P2, P3), i = (1,2,\dots,15) \\ h_i(P) = h_i(P1, P2, P3), i = (1,2,\dots,15) \end{array} \right. \quad (6)$$

Where  $\min M(P)$  and  $\min D(P)$  are the objective functions and P is the design variables (P) and  $h_i(P)$  are state variables, which is the constraint condition. Then the multi-objective optimization problem of the support size is transformed into finding the appropriate design variable combination P1 and P2, so that the objective function M (P) and D (P) can reach the optimal value.

## 6. Support Optimization

Multi-objective optimization problem is a challenging optimization problem, which exists widely in scientific research and engineering applications (Wang et al.,2016)<sup>[14]</sup>.For most optimization problems, the orientation of each objective function is conflicting, so that there is no unique global optimal solution for the multi-objective optimization problem. However, there is a solution that cannot be further optimized for some objective functions and has no effect on the orientation of other objective functions, which is called the non-inferior optimal solution (Zhu et al.,2015).Optimal design based on response surface is a series of calculations based on response surface model.

### 6.1 Multi-objective genetic algorithm

Multiobjective genetic algorithm (MOGA) is one of the most representative multiobjective evolutionary algorithms based on pareto method.It sorts all the individuals in the population by the concept of "Pareto optimal individual", according to which the selection operation in the optimization process is carried out, so that the Pareto optimal individual in front has more chances to inherit to the

next generation. After a certain number of cycles, the Pareto optimal solution of the multi-objective optimization problem can be obtained (Li et al.,2016;Wu et al.,2017).

Double-click Optimization into the optimization setting interface and select the MOGA method to generate 100 screening samples. Set the maximum allowable Pareto ratio to 70, the number of population to 100, and the maximum number of iterations to 20.The parameter types of the three optimization objectives are set: the mass and the total shape variables are set to the minimum output, the equivalent stress is set to the maximum output, and the constraint maximum stress is not greater than 288MPa.Because the main goal of the optimization is to achieve the lightweight of the scaffold, the quality is set as the highest priority in "Objective Importance", followed by the largest shape variable and the lowest priority of the maximum equivalent stress. The parameter types and weight settings for the optimization goal are shown in Table 3. Update the optimization, and the optimization table will show the three candidate points for the specified target as shown in Table 4.

Table 3 optimizing objective type and weight table

object function	optimization objective	weight
Support mass	minimality	Higter
Maximum shape variable	Minimality; $\leq 6\text{mm}$	Default
Maximum equivalent stress	$\leq 288\text{MPa}$	Lower

Table 4 Optimization candidate points

Candidate point	P1/mm	P2/mm	Mess/kg	Deformation/mm	Stress /MPa
1	5.79	40.279	2122.6	6.7267	283.35
2	4.51	40.185	2123	6.4439	286.09
3	4.03	39.06	2127.4	4.2268	165.43

Table 5. Comparison of results of calculation and optimization

	P1/mm	P2/mm	Mass/kg	deformation/mm	stress /MPa
Optimization result	4.51	40.185	2123	5.2865	156.85
computing result	4.51	40.185	2123	5.2544	156.96

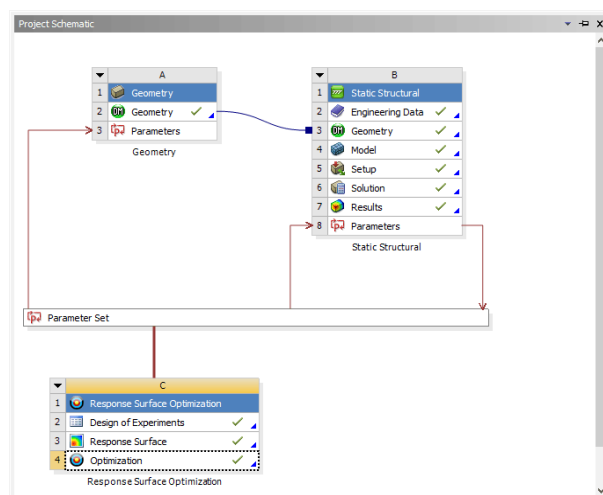


Figure 13 Optimization flow chart



### 6.2 Optimization process

Different modules in Workbench have different functions. By adding different analysis modules, the data can be shared in the software platform(Cheng and Huang,2015).For the purpose of this paper, the analysis flow of multi-objective optimization design based on response surface is shown in figure 13.Figure 14 is the tradeoff point diagram of the optimization result, and the blue point is the optimum design point.

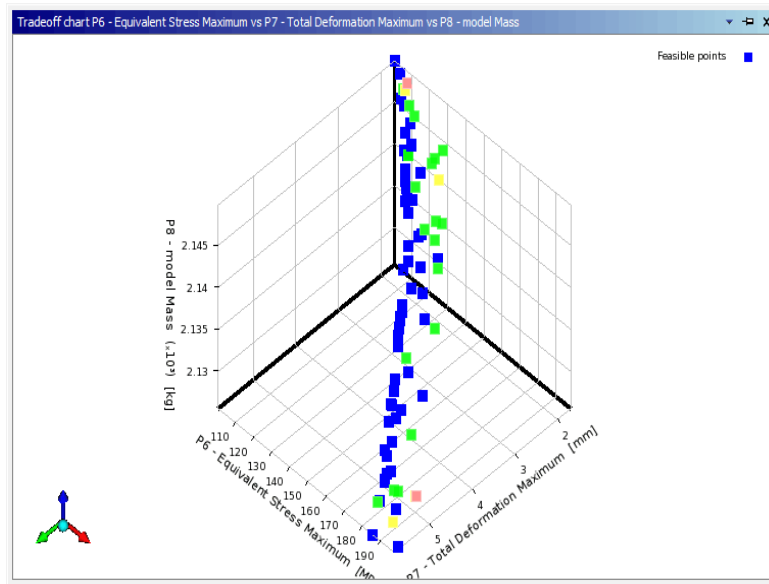


Figure 14 tradeoff scatter diagram

### 6.3 Optimization result

In the 3 set of candidate points, the more the number of stars, the better the effect is. From a set of samples(a certain number of design points), the best design point is obtained as candidate point 2 (Wang,2015):

Table 6. Optimum design point

	P1/mm	P2/mm
size	4.51	40.185

The optimal scheme obtained by using Response Surface Optimization for optimal design is based on the prediction of response surface, and it is not the finite element analysis of the model directly, and errors will inevitably occur. The more the sample size is in goal-driven optimization, the closer the optimization result to the optimization goal (Xia et al.,2015).The optimal candidate point is selected as the design point to be inserted into the parameter setting space. After the complete parameter modeling, the statics analysis process obtains the real support mass, stress and shape variable value. The results of calculation and optimization are for example, Table 5.

The error is between 0 and 0.68%, so the recalculated results are in good agreement with the predicted values from the response surface. Taking into account the manufacturing accuracy in actual production, P1=4.5mm P2=40.2 mm. Using the correlation between workbench and SolidWorks, the software reconstructs the parameterized model and reconducts the stress analysis. The result of finite element analysis of the optimized model is shown in Fig. 14 and 15 (Feng et al.,2013;Meng et.al.,2014;Shi,2016;Shi et al.,2015).

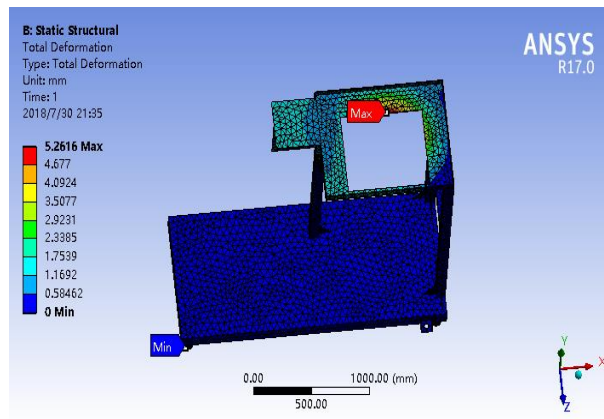


Figure 15 deformed cloud chart after optimization

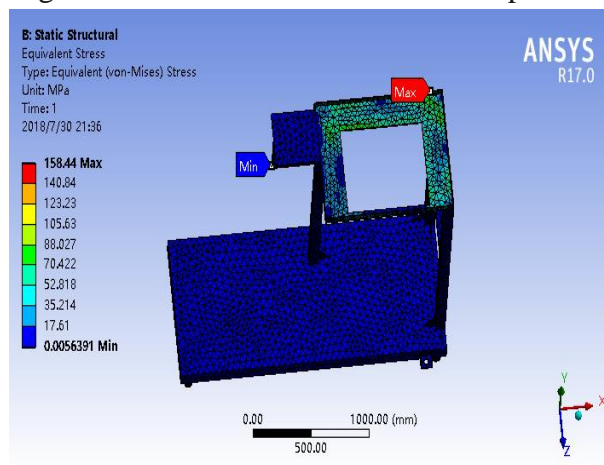


Figure 16 stress cloud after optimization

The results before and after optimization are compared in Table 7. After optimization, P2 increases and P1 decreases. The optimization results show that through the optimization design of the dimension parameters, the overall mass of the fully automatic grain baling machine is reduced by 0.95mm, the maximum deformation of the support is 5.2616mm, and the maximum equivalent stress is 158.44MPa. Although it is more than before the optimization, it is still less than the allowable stress 288MPa of the material, and the maximum variable is also the minimum value within the allowable range. It makes full use of the material performance and avoids the waste of materials. The optimized design not only meets the practical requirements of the scaffold, but also achieves the goal of lightweight, material saving and cost reduction.

Table 7. Optimization results

	P1/mm	P2/mm	Mass/kg	stress /MPa	deformation/mm
Pre optimization	5	35	2143.3	123.62	2.2187
postoptimality	4.5	40.2	2122.9	158.44	5.2616

## 7. Conclusion Remarks

In order to avoid the overweight of the fully automatic grain baling machine, the optimum design of the support is carried out in the light weight under the condition that it can provide sufficient strength and stiffness. Firstly, Solid works is used to model the scaffold. In addition, through the static analysis of the support, the maximum stress and the maximum deformation are obtained, and the weak link of the support structure is determined. On this basis, the relevant dimensions are set as optimization variables for multi-objective optimization design. And finite element analysis and experimental verification are conducted for the optimization result and the support structure obtained meets the

design requirement (Arunkumar et al.,2017).The lightweight target is achieved, and the quality of the scaffold is reduced (0.95%), the cost is reduced, and the material is saved. Taking the three-dimensional model of Solid works scaffold as an example, this paper introduces the multi-objective optimization function of Ansys Workbench. This function can be applied to mechanical design, optimization of all kinds of 3D models and 3D research.

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