RSM Based General Optimization Methods and Application on Reciprocating Pump Design

Yangdong Wu, Lifang Wang

Lab of Contemporary Manufacturing Technology Guizhou University

Reciprocating Pump Technology Institute Benxi Water Pumps Co., ltd

Qxyd2000@yahoo.com.cn

yd_798@hotmail.com

***Abstract*-This paper proposes that using response surface methodology (RSM) to solve multiple variables problems, for multiple responses, transforming each response into desirability function and combined them to an overall desirability function, so the multiple responses can be changed into one single function, the overall desirability is solved through intelligent algorithm. At last section, a study case is given to show the feasibility of the methodology proposed in this paper.**

Keywords-Response surface methodology; Multiresponse optimization; Desirability function; Intelligent algorithm; Reciprocating pump

I. INTRODUCTION

Product robust design is a fine technique to improve product quality, since G.Taguchi put forward the method, many study commit themselves to improve on the robust design technique through statistics analysis method [1], many methods introduce response surface methodology(RSM) to instead of signal noise ratio method which was brought forward by G. Taguchi [2]. RSM is a sort of statistics techniques which are useful for the modeling and analysis in Multi variable problem, it could find out the relation among factor and quality characteristic (viz. response) and then implement optimization to gain various factor levels which make quality characteristic optimization. Figure 1 shows the RSM robust design principle.

But in this domain, product design and optimization were for single quality characteristic previously, along with product become more and more complicated and diversifications of customer requirement, product quality characteristics possess Multi target frequently[3]. So multiresponse optimization shows its important academic value and applied value progressively. Multiresponse optimization need optimize multi-responses at the same time, for resolve the question, we may transform multi-response into a single response by mathematics method and then optimize the single response [4]. This paper presents rationale of response surface methodology, multi-response transforming method based on desirability function and overall desirability function optimization using intelligent algorithm.

Reciprocating pump belongs to positive displacement pump, it make the liquid medium volume change periodically by plunger reciprocation. Reciprocating pump suit to transport high pressure, low flow and high viscosity liquid, but it cannot transport corrosive liquids usually. Sometimes, it would be driven by steam engine for transporting flammable liquid and explosive liquid. Reciprocating pump could start without injecting liquid, so reciprocating pumps possesses self-priming capability, but the suction capability would change along with the atmospheric pressure, the liquid nature and temperature, so the installation altitude of reciprocating pump is restricted. Reciprocating pump discharge cannot be adjusted by valves, but it should be changed through bypass pipe or changing the operation frequency of the piston, changing the piston stroke. Before reciprocating pump starting, discharge pipe valve must be open. Reciprocating piston connects with motor by pump crankshaft and connecting rods. The pump can be driven by electromotor or steam engine.

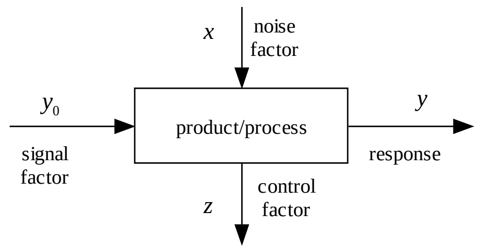

Figure 1 RSM Robust Design Principle

II. RATIONAL OF RESPONSE SURFACE METHODOLOGY

Response surface methodology is a collection of mathematical and statistical techniques that are useful for modeling and analysis of problems in which a response of interest is influenced by several variables and where the objective is to optimize this response. We use the RSM to model the response of multiple quality characteristic caused by various control and noise factors [5]. There control factor is design factor that designer could control them and noise factor is un-control factor that influence quality characteristic.

The RSM is an important branch of experimental design. It is a critical technology for optimizing product performance and improving the design formulation of new products. Response surface methods can lead to a rapid and accurate exploration of the parameter space and to the estimation of optimum conditions with a small expenditure on experimental data. The experimental design, multivariate regression analysis, and optimization techniques form the foundation of response surface methodology.

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Experimental design is used to select parameter combinations for efficient experimentation [6]. Using the resulting data, a second-order estimation model is constructed using regression analysis techniques relating the output response surface to input parameters.

The second-order model was applied widely at present. a fitted second-order model is given by

$$\hat{y} = \hat{\beta}_0 + \sum_{i=1}^{n} \hat{\beta}_i x_i + \sum_{i=1}^{n} \hat{\beta}_{ii} x_i^2 + \sum_{i<j} \hat{\beta}_{ij} x_i x_j \quad (1)$$

It could express by matrix as

$$\hat{y} = \hat{\beta}_0 + x^T b + x^T Bx \quad (2)$$

where

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}, \quad b = \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \vdots \\ \hat{\beta}_n \end{bmatrix}, \quad B = \frac{1}{2} \begin{vmatrix} 2\hat{\beta}_{11} & \hat{\beta}_{12} & \cdots & \hat{\beta}_{1n} \\ \hat{\beta}_{21} & 2\hat{\beta}_{22} & \cdots & \hat{\beta}_{2n} \\ \vdots & \vdots & & \vdots \\ \hat{\beta}_{n1} & \hat{\beta}_{n2} & \cdots & 2\hat{\beta}_{nn} \end{vmatrix}$$

xi(i=1,2, … ,n) are n independent input variables. The model regression coefficient could be calculated by least square method.

Response surface methodology could fit the model that include control and noise factors, when we carry out experimental design, two kinds of factors may arrange on one array. Here response surface model could be present by

$$\hat{y}(x,z) = y(x,z) + \varepsilon_y \quad (3)$$

Through coding transforming, x and z could define in region

R_x ={x: $-1 \le x_i \le +1$, i = 1,2,$\cdots$,n}

R_z ={z: $-1 \le z_i \le +1$, i = 1,2,$\cdots$,k}

If two kinds of factors were defined as

xT = (x1,x2,$\cdots$,xn) , zT = (z1,z2,$\cdots$,zk)

the general second-order polynomial regression model may be written as

$$y(x,z) = \beta_0 + x^T \beta + x^T Bx + z^T Rz + z^T \gamma + z^T Dx + \varepsilon_y \quad (4)$$

the empirically fitted second-order model may be written as

$$\hat{y}(x,z) = b_0 + x^T b + x^T \hat{B} x + z^T \hat{R} z + z^T \hat{\gamma} + z^T \hat{D} x \quad (5)$$

where b, $\hat{B}$, $\hat{R}$, $\hat{\gamma}$ and $\hat{D}$ are appropriate vectors or matrices of unknown regression parameters.

The mean response function $\hat{m}(x)$ is as follow

$$\hat{m}(x) = k\int_{R_z} \hat{y}(x,z)dz = b0 + xTb + xT\hat{B}x + \frac{1}{3}\mathrm{tr}\,\hat{R} \quad (6)$$

where tr $\hat{R}$ is the trace of the matrix $\hat{R}$, k is a constant, $k^{-1} = \int_{R_z} dz$, z is usually uniformly distributed over region Rz.

The variance response function can be calculated as

$$\hat{v}(x) = k\int_{R_z} [\hat{y}(x,z) - \hat{m}(x)]^2 dz = (\hat{\gamma} + \hat{D}x)^T (\hat{\gamma} + \hat{D}x)/3 + A \quad (7)$$

where

$$A = \frac{1}{45}[4\sum_{j=1}^{m} r_{jj}^2 + 5\sum_{j=1}^{m-1}\sum_{k=j+1}^{m} r_{jk}^2]$$

r_{jk} is the jth row and kth column element of the matrix $\hat{R}$.

$$\hat{R} = \frac{1}{2}\begin{bmatrix} 2r_{11} & r_{21} & \cdots & r_{k1} \\ r_{12} & 2r_{22} & & r_{k2} \\ \vdots & \vdots & & \vdots \\ \vdots & \vdots & & \vdots \\ r_{1k} & r_{2k} & & 2r_{kk} \end{bmatrix}$$

When using the response surface model, in order to sure that the regression is significant, analysis of variance can be used to indicate that the regression of experimental data is significant for the regression analysis.

The basic of response surface methodology is design of experiments (DOE). Design of experiments or experimental design is the design of any information-gathering exercises where variation is present, whether under the full control of the experimenter or not. However, in statistics, these terms are usually used for controlled experiments.

Design of experiments is thus a discipline that has very broad application across all the natural and social sciences. The DOE methodology ensures that all factors and their interactions are systematically investigated. Therefore, information obtained from a DOE analysis is much more reliable and complete than results from one-factor-at-a-time experiments that ignore interactions and may lead to incorrect conclusions.

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The figure 2 shows the face-centered central composite design for three factors, a typical Design of experiments.

When the experimenter wants to investigate more factors (for instances, more than 4 factors) in an experiment one cannot expect to obtain a good result without the use of modern experimental designs. We need some efficient fractional factorial designs, as central composite design, orthogonal design etc.

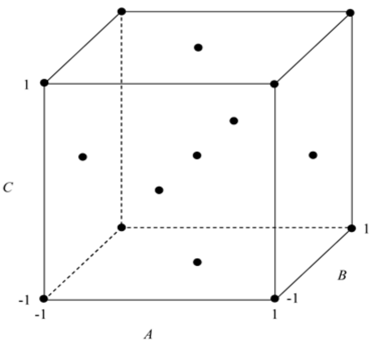

Figure 2 Face-Centered Central Composite Design for Three Factors

The Uniform design is another such efficient fractional factorial design. It has been successfully used in various fields such as chemistry and chemical engineering, pharmaceutics, quality engineering, system engineering, survey design, computer sciences and natural sciences. The uniform design has been recognized as an important space-filling design by the international community.

III. MULTIPLE RESPONSE TRANSFORMATION

For a multi-response problem, the goal is to find the setting of the design variables that achieve an optimal balance of the response variables [7]. A quantitative method that can be used to combine multiple responses into one single function and attempt to find the optimal balance, namely desirability function method[8], each response function is transformed into a desirability function. Derringer improved this method.

For various design requirements, several desirability functions could be defined. For nominal the best, desirability function is given as

$$d_i(\hat{y}_i) = \begin{cases} \left(\dfrac{\hat{y}_i - l_i}{t_i - l_i}\right)^{s_i} & l_i \le y_i < t_i \\ \left(\dfrac{\hat{y}_i - h_i}{t_i - h_i}\right)^{p_i} & t_i \le y_i \le h_i \\ 0 & \text{other} \end{cases} \tag{8}$$

For the smaller the better, desirability function is given as

$$d_i(\hat{y}_i) = \begin{cases} 0 & \hat{y}_i > h_i \\ \left(\dfrac{\hat{y}_i - h_i}{l_i - h_i}\right)^{q_i} & l_i \le \hat{y}_i \le h_i \\ 1 & \hat{y}_i < l_i \end{cases} \tag{9}$$

For the larger the better, desirability function is given as

$$d_i(\hat{y}_i) = \begin{cases} 0 & \hat{y}_i < l_i \\ \left(\dfrac{\hat{y}_i - l_i}{h_i - l_i}\right)^{q_i} & l_i \le \hat{y}_i \le h_i \\ 1 & \hat{y}_i > h_i \end{cases} \tag{10}$$

where di is a desirability function of $\hat{y}_i$, hi is maximum value, li is minimum value, ti is target value, si, pi and qi are arbitrary plus constant.

All the individual desirability functions are combined to form a composite desirability function:

$$D = \left(\prod_{i=1}^{n} d_i\right)^{1/n} \tag{11}$$

The overall desirability function using weighted geometric mean of the di can be defined as

$$D = \left(\prod_{i=1}^{n} d_i^{w_i}\right)^{1/\sum w_i} \tag{12}$$

where w_i is weight of $\hat{y}_i$, $\sum w_i = 1$.

The levels of various factors and $\hat{y}_i$ corresponding to the maximum value of D represent the optimum solution and its response.

IV. OVERALL DESIRABILITY FUNCTION OPTIMIZATION ALGORITHM

The goal of multi-response problem is to find the setting of the design variables that achieve an optimal balance of the response variables [9]. Desirability function method can be used to combine multiple responses into one single function and attempt to find the optimal balance. Each response function is transformed into a desirability function. Here we adopt the three kinds of desirability functions which were discussed in paper of Hezheng [10], they may adapt to various design requirements.

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All the individual desirability functions are combined to form an overall desirability function the overall desirability function can be defined as weighted geometric mean of the individual desirability. The levels of various factors and response value corresponding to the maximum value of overall desirability function represent the optimum solution and its response.

Multiple response optimization is complicated, the overall desirability function is a nonlinear function usually, design variable and its restriction include both continuous variable and disperse variable, so it is difficult to solve the problem using ordinary optimization algorithm. An intelligent optimization method, such as simulated annealing (SA) can be used to optimize the overall desirability function.

Simulated annealing is a generalization of a Monte Carlo method for examining the equations of state and frozen states of n-body systems [11]. The concept is based on the manner in which liquids freeze or metals recrystallize in the process of annealing. SA was proposed by Metropolis in 1953 firstly, he developed the method for solving optimization problems that mimics the way thermodynamic systems go from one energy level to another. This method require that a system of particles exhibit energy levels in a manner that maximizes the thermodynamic entropy at a given temperature value. Also, the average energy level must be proportional to the temperature, which is constant.

Kirkpatrick originally thought of using SA on computer related problems in 1983. He applied SA to various optimization problems. SA is a good algorithm because it is relatively general and tends to not get stuck in local minimum or maximum.

SA is based on the annealing of metals. Metropolis created an algorithm, which is also known as the Metropolis rule of probability, to simulate annealing through a series of moves. During each move, the system has some probability of changing its current configuration to a worse one. Metropolis Criterion change configurations is what enable SA to jump out of local maxima or minima where most algorithms get stuck. Several parameters need to be included in an implementation of SA.

The original Metropolis scheme was that an initial state of a thermodynamic system was chosen at energy E and temperature T, holding T constant the initial configuration is perturbed and the change in energy dE is computed. If the change in energy is negative the new configuration is accepted. If the change in energy is positive it is accepted with a probability given by the Boltzmann factor exp -(dE/T). This processes is then repeated sufficient times to give good sampling statistics for the current temperature, and then the temperature is decremented and the entire process repeated until a frozen state is achieved at T=0.

By analogy the generalization of this Monte Carlo approach to combinatorial problems is straight forward. The current state of the thermodynamic system is analogous to the current solution to the combinatorial problem, the energy equation for the thermodynamic system is analogous to at the objective function, and ground state is analogous to the global minimum. Furthermore, avoidance of entrainment in local minima (quenching) is dependent on the "annealing schedule", the choice of initial temperature, how many iterations are performed at each temperature, and how much the temperature is decremented at each step as cooling proceeds. Wangdingwei analyzed SA astringency in his document [12]. The flow of SA is illustrated in figure 3.

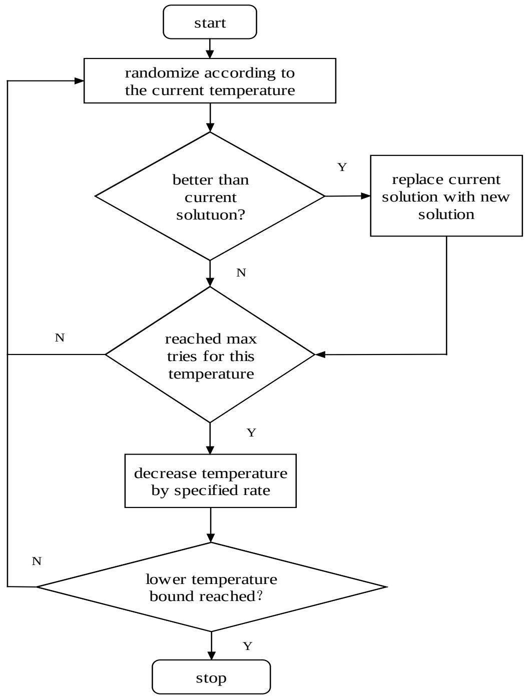

Figure 3 Flowchart of the SA

V. RECIPROCATING PUMP GENERAL DESIGN USING MULTIPLE RESPONSE OPTIMIZATION

Reciprocating pump consists of transmission parts, hydraulic parts, pipelines subassembly and accessory and so on, each portion contains relevant components. It has abundant variety and less production batch, and its performance parameter is often a series. The figure blow shows a typical three plungers reciprocating pump.

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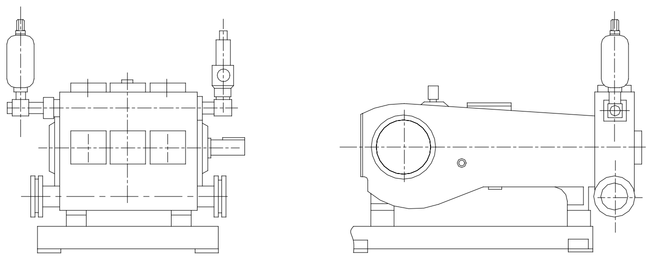

Figure 4 Three Plungers Reciprocating Pump

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Reciprocating pump original design parameters includes discharge rate (Q), discharge pressure (Pq), number of plunger (Z), number of action (K), volume efficiency (ηv), power of motor(P), structure mode, operation temperature etc. On the basis of original design parameter, we can identify motor power and master structure parameter, i.e. plunger diameter (D), plunger stroke (S) and pump rate (n), accordingly transmission end, hydraulic end, pipeline subassembly and accessory may be designed and structure dimension of these parts may be gained.

Figure5 illustrates reciprocating pump principle. When it works, the piston moves from left to right, form a negative pressure pump cylinder, then the suction tank fluid through the valve into the pump cylinder. When the piston moves from right to left, the liquid of cylinder is squeezing, and the pressure increasing, liquid discharged from the discharge valve. A reciprocating piston, if suction and discharge fluid known as a work cycle, the pump called the single-action pump. When the piston rounds one circle, the suction and discharge of pump are twice, the pump known as double-acting pump. Piston from one end to another end, called a stroke.

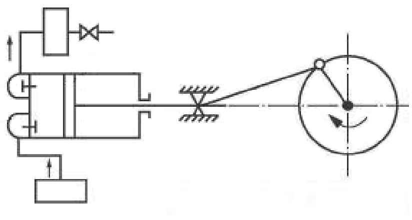

Figure 5 Reciprocating Pump Schematic Diagram

The key of reciprocating pump design is master structure parameter design. The design of master structure parameter decide whether whole dimension is harmonious and technology parameter is matching, it decide whole design project of product and become the important foundation of particular design of other parts. Thus design of master structure parameter is the most important portion of reciprocating pump design. Figure 6 shows relation among reciprocating pump major parts.

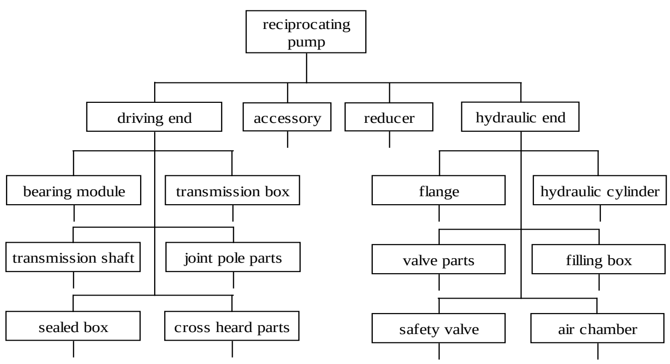

Figure 6 Reciprocating Pump Parts (Partial)

Master structure parameter ought to satisfy the requirement of product performance parameter, and make product have enough life and reliability and maintenance convenience. In reciprocating pump design, consumer requirement may express by two basal performance parameters, namely displacement and pressure. Pressure is never related to displacement, it lies on characteristic of equipment, and that displacement lies on master structure parameter, the same displacement may make up of different master structure parameter. For obtaining right master structure parameter, we should choose appropriate average speed of plunger firstly, then revolution of crank and stroke length are gained, finally, according to the ratio of stroke length and plunger diameter, regulating these parameter and gaining plunger diameter, so a group of right master structure parameter are found. The parts structure design could operate based on master structure parameter.

We would design a reciprocating pump, its discharge rate is 10.2m3/h and discharge pressure is 11Mpa. According as reciprocating pump design theory, power(P), torque(T) and plunger fore(F) are quality characteristics, the factors that would be calculated in design are plunger diameter(D), plunger stroke(S), pump rate (express with n) and volume efficiency(express with η_v), pump discharge rate(express with Q) is considered as a restriction.

In design process, discharge rate can be calculated as

$$A \cdot S \cdot n \cdot D \cdot \eta_V = 712 \tag{13}$$

where A is section area of plunger.

The formulations of P, T and F are given in reciprocating pump [13]. Due to formulation of F is simpler, we calculate response surface of P and T only, desirability function of F could be defined directly.

According to design criterion of reciprocating pump, control factors include D, n, S and η_V, system restriction are plunger average speed(um) and ratio of plunger stroke to plunger diameter(ψ), their range of value from references to reciprocating pump. Various factors and system restriction are listed in table Ⅰ.

TABLE I PARAMETER AND RANGE

Parameter	Range
Factors: D N S η_v	 25~50 mm 390~420 min^{-1} 70~95 mm 0.87~0.97
System restrict: U_m= S N/30 ψ = S/D	 0.5~1.3 m/s 1.0~3.5

In experimental design of response surface, uniform design is applied, there are four factors in the experiment, so we use uniform design table $UL_{18}(6^4)$ [14], it is shown in table Ⅱ.

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TABLE II 4 FACTORS 6 LEVELS UNIFORM EXPERIMENT DESIGN

	1	2	3	4
1	3	2	3	6
2	2	1	6	3
3	4	5	6	1
4	3	6	1	2
5	3	4	5	4
6	4	1	4	5
7	2	3	4	1
8	5	6	3	4
9	1	4	3	2
10	6	2	5	2
11	4	3	2	3
12	6	5	4	3
13	5	3	6	6
14	1	2	1	4
15	5	1	2	1
16	1	6	5	5
17	6	4	1	5
18	2	5	2	6

According to design theory of reciprocating pump, the values of level of each factor is shown in table III, the coefficient of response surface model is obtained by the least square method. We use v instead of η_v in following parts of the paper for predigest expression.

TABLE III LEVELS OF EARCH FACTOE

	1	2	3	4	5	6
D	25	30	35	40	45	50
S	70	75	80	85	90	95
n	395	400	405	410	415	420
v	0.87	0.89	0.91	0.93	0.95	0.97

The fitted second-order model could be obtained using the least square method, the figure 7 shows the regression result of Q, Figure 8 illustrated the relation among q, d and s.

Response Surface Regression: q versus d, s, n, v

The analysis was done using coded units.

Estimated Regression Coefficients for q

Term	Coef	SE Coef	T	P
Constant	1.34958	0.090767	14.869	0.000
d	0.36395	0.035696	10.196	0.000
s	0.05495	0.015207	3.613	0.006
n	0.03792	0.013845	2.739	0.023
v	0.03275	0.016219	2.020	0.074
d*d	0.11350	0.004060	27.958	0.000
d*s	0.09491	0.004067	23.335	0.000
d*n	0.01189	0.003544	3.355	0.008
d*v	0.03067	0.004323	7.095	0.000

S = 0.04241 R-Sq = 100.0% R-Sq(adj) = 100.0%

Analysis of Variance for q

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	8	151.922	151.92197	18.99025	10556.66	0.000
Linear	4	148.989	0.19221	0.04805	26.71	0.000
Square	1	1.274	1.40607	1.40607	781.63	0.000
Interaction	3	1.659	1.65904	0.55301	307.42	0.000
Residual Error	9	0.016	0.01619	0.00180		
Total	17	151.938				

Unusual Observations for q

Obs	StdOrder	q	Fit	SE Fit	Residual	St Resid
10	10	9.790	9.848	0.034	-0.058	-2.23 R

R denotes an observation with a large standardized residual.

Figure 7 Regression Analysis Result

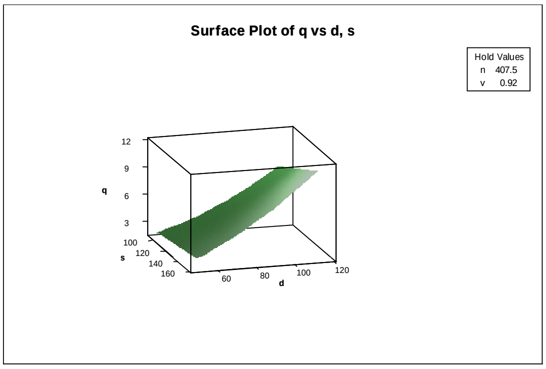

Figure 8 Q in Relation to D and S

The fitted second-order model are listed as

P=5.50006+1.29446d+0.07496s-0.01314n+0.03904v+ 0.40624d2+0.35426ds+0.03897dn+0.10843dv+0.02305sn +0.02383nv (14)

T=119.503+35.301d+4.231s+2.494n+2.433v+9.635d2+ 8.117ds-0.706dn+2.708dv (15)

Then in term of design criterion, each desirability function can be defined as

$$d_P = \begin{cases} 0, p < 33 \\ 0.167P - 5.5, 33 \le p \le 39 \\ 1, p > 39 \end{cases} \tag{16}$$

$$d_T = \begin{cases} 0, T < 710 \\ (T-710)/240, 710 \le T \le 950 \\ 1, T > 950 \end{cases} \tag{17}$$

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$$d_F = \begin{cases} 1, F < 17.5 \\ 8 - 0.4F \quad ,17.5 \le F \le 20 \\ 0, F > 20 \end{cases} \tag{18}$$

The weight value of every response is established by designer, are 0.4, 0.3 and 0.3. So overall desirability function is

$$D_{(P,T,F)} = (d_P)^{0.4}(d_T)^{0.3}(d_F)^{0.3} \tag{19}$$

The optimization problem is as

$$\max \quad D_{(P,T,F)} = (d_P)^{0.4}(d_T)^{0.3}(d_F)^{0.3}$$

$$\begin{aligned} s.t.\quad & 300 \le n \le 500 \\ & 0.87 \le v \le 0.97 \\ & 1.0 \le \psi \le 3.5 \\ & 0.5 \le u_m \le 1.3 \\ & q = 10.2 \end{aligned}$$

Using simulated annealing, the optimizing result is listed in tableⅣ.

TABLE IV DESIGN RESULT

Varible	D = 46mm, S=92mm, n=403min^{-1}, v=0.92
Response	P=36.7Kw, T= 869.7Nm, F=18.3KN
Desirability	d_p=0.617, d_T=0.665, d_F=0.680, $D_{(P,T,F)}$ = 0.650

VI. CONCLUSION

Response surface methodology is useful for modeling and anlysis of multiple variables problems, we use the RSM to model the response of multiple quality characteristics caused by various factors, and transform response into desirability function, simulated annealing is used to solved overall desirability function, so a multi-response problem is changed into one single function problem. The desirability function method is attractive because it is intuitive and simple, simulated annealing is relatively general and tends to not get stuck in local minimum or maximum, it is one of best algorithm. The case study shows that this paper presents the method which can solve multiple response optimization problems preferably.

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Yangdong Wu was born in 1969, in Benxi, P.R.China. in 2008, he graduated and obtained Doctorate Degree in Zhejiang University, Hangzhou, P.R.China. His major field of study is Contemporary Manufacturing Technology and Mass Customization. He is with the Lab of Contemporary Manufacturing Technology, Guizhou University, Guiyang, P.R.China.

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