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ПОИСК ОБЛАСТИ ОПТИМАЛЬНЫХ УСЛОВИЙ ПО РЕЗУЛЬТАТАМ ПАССИВНОГО ЭКСПЕРИМЕНТА

В статье рассмотрен метод, позволяющий по результатам экспериментов, выполненных по ротatableльным центрально-композиционным планам, построить линейную модель, описывающую область оптимума, и исследовать полученную модель на экстремум. Рассмотрен поиск области оптимальных условий по результатам пассивного эксперимента, описывается алгоритм обработки результатов экспериментов для получения модели и проверки ее на адекватность.

Пассивный эксперимент, факторы, область оптимальных значений, коэффициенты модели, дисперсия адекватности, критерий оптимизации, адекватная модель.

The article describes a method, that allows to build a linear model and explore the obtained model for revealing the extreme point according to the experiment results carried out with the help of rotatable central composite plans. This model describes the optimum area. The article considers the search for the optimal conditions according to the passive experiment results and describes the algorithm of processing experiment results for the model as well as tests it for the adequacy.

Passive experiment, factors, optimum area, model coefficients, approximation dispersion, optimization criterion, adequate model.

1. Introduction

Upon studying the extreme field the interest is often to estimate not coefficients of the obtained regression model, but the response function itself. Moreover, in practice the regression model can be often considerably simplified by rotating the coordinate axes, i.e. coordinate transformation [1]. Rotatable planning, providing a prediction error of the output value by the regression equation, dependent only on the distance of the factorial experiment point to the experiment center, allows to predict the response function value with the same accuracy and, consequently, to transform the coordinate system to facilitate the regression equation [2].

Finding optimal regions for the object is the most important practical task. Most often in the context of the multivariate experiment it is required to find those factor score x_i in which the system response y takes the score y_{max} and y_{min} .

2. Research methodologies

Thus, the objective response function is constructed:

$$y = y(x_1, x_2, \dots, x_k), \quad (1)$$

and the optimization problem is reduced to finding $x_{1\text{ opt}}, x_{2\text{ opt}}, \dots, x_{k\text{ opt}}$ providing the objective function extremum:

$$y_i = y(x_{1\text{ opt}}, x_{2\text{ opt}}, \dots, x_k) = y_{\min} (y_{\max}). \quad (2)$$

Furthermore, additional restrictions are imposed on the factor score:

$$y(x_1, x_2, \dots, x_k) \{ \geq, =, \leq \} R_i, \text{ where } i = 1 \dots r. \quad (3)$$

Thus, the optimization problem is to find the response function extremum provided that the function itself is a priori unknown.

In practice, we often have to predict conditions of subsequent experiments to achieve the optimal region on the basis of a limited number of passive experiment data, i.e. on the basis of the experiment results carried out without the preliminary plan [3].

To find the optimal region according to the passive experiment it is necessary to follow the next steps:

1. To find the score of the imputed value R using the next formula:

$$R_j = \sum_{i=1}^N (x_{ij} - \bar{x}_j) y_i, \quad (4)$$

where x_{ij} is the value of j factor in i experiment; $\bar{x}_j$ is the central value of j factor based on the results of N experiments; y_i is the optimization criterion value in i experiment.

2. To determine the conditions for new experiences $(N+1)$, using the formula

$$x_j^{N+1} = \bar{x}_j \pm KR_j, \quad (5)$$

where x_j^{N+1} is the value of j factor in $N+1$ experiment; K is the scaling factor (it is the same for all the factors and it should provide the physical realizability of the experiment).

In the formula (5) signs “+” or “-” are put in the search, according to the maximum or minimum of the objective function. It will be observed that this method may give inaccurate results with a small number of experiments and with low reproducibility (with large distortion).

Let's consider the method implementation with an example: the passive experiment results (table 1) for the purpose of increasing the output production quality (y) it was necessary to determine the most preferred factor values, in our case we should determine the chemical composition value affected manufactured steel to a greater extent: $C/\%$ (x_1), $CaO\ com/kg(x_2)$, $t\ last/C^0$ (x_3), Graphite/kg(x_4), $MnC17$ ($P35$) and ($P50$)/kg (x_5), argon consumption/ m^3 (x_6), processed spar $CaF2/kg$ (x_7), $Vl\%$ (x_8), $Si/\%$ (x_9).

According to the formula (1) let's determine the imputed value R_j :

$$R_1 = (0,802 - 0,802) \cdot 0,6154 + (0,827 - 0,802) \cdot 0,5792 + (0,728 - 0,827) \cdot 0,5905 + (0,802 - 0,728) \cdot 0,6171 + (0,759 - 0,802) \cdot 0,5954 + (0,855 - 0,759) \cdot 0,5104 + (0,871 - 0,855) \cdot 0,6554 + (0,846 - 0,871) \cdot 0,5601 + (0,857 - 0,846) \cdot 0,6085 + (0,83 - 0,857) \cdot 0,7122 + (0,825 - 0,83) \cdot 0,7082 = 0,0055;$$

then: $R_2 = 36,9017$; $R_3 = 0,4649$; $R_4 = 49,6029$;

$R_5 = -22,441$; $R_6 = -0,0347$; $R_7 = -5,9973$;

$R_8 = -0,0001$; $R_9 = 0,0011$.

1. Let us assume that $K = 0,05$, then the conditions of experiment 10 will be:

$$x_1^9 = 0,8184 + 0,05 \cdot 0,0055 = 0,8186;$$

$$x_2^9 = 449,55 + 0,05 \cdot 36,9017 = 451,3905;$$

$$x_3^9 = 1531,36 + 0,05 \cdot 0,4649 = 1531,387;$$

$$x_4^9 = 812 + 0,05 \cdot 49,6029 = 814,4801;$$

$$x_5^9 = 154,091 + 0,05 \cdot (-22,441) = 152,9689;$$

$$x_6^9 = 0,1088 + 0,05 \cdot (-0,0347) = 0,1071;$$

$$x_7^9 = 595,909 + 0,05 \cdot (-5,9973) = 595,6092;$$

$$x_8^9 = 0,0014 + 0,05 \cdot (-0,0001) = 0,0014;$$

$$x_9^9 = 0,1939 + 0,05 \cdot 0,0011 = 0,194.$$

The implementation of experiment 10 in production environment allowed to achieve the maximum value of the output parameter Y which is equal to 0,7122 (71 %).

2. In order to check whether the area of optimal values of input factors in experiment 10 is reached, we will plan another experiment. The experiment conditions are determined by the results of all previous experiments 1-10.

$$R_1 = (0,802 - 0,8184) \cdot 0,6154 + (0,827 - 0,8184) \cdot 0,5792 + (0,728 - 0,8184) \cdot 0,5905 + (0,802 - 0,8184) \cdot 0,6171 + (0,759 - 0,8184) \cdot 0,5954 + (0,855 - 0,8184) \cdot 0,5104 + (0,871 - 0,8184) \cdot 0,6554 + (0,846 - 0,8184) \cdot 0,5601 + (0,857 - 0,8184) \cdot 0,6085 + (0,83 - 0,8184) \cdot 0,7122 + (0,825 - 0,8184) \cdot 0,7082 = 0,0013;$$

then: $R_2 = 0,1245$; $R_3 = 0,8916$; $R_4 = 6,3292$;

$R_5 = 0,0478$; $R_6 = 0,0048$;

$R_7 = -18,3314$; $R_8 = -7,5541$; $R_9 = 0,0031$.

Then, with the same value of the scaling factor we will get the following:

$$x_1^9 = 0,8184 + 0,05 \cdot 0,0013 = 0,8184;$$

$$x_2^9 = 449,55 + 0,05 \cdot 0,1245 = 449,55;$$

$$x_3^9 = 1531,36 + 0,05 \cdot 0,8916 = 1531,408;$$

$$x_4^9 = 812 + 0,05 \cdot 6,3292 = 812,3165;$$

$$x_5^9 = 154,091 + 0,05 \cdot 0,0478 = 154,0933;$$

$$x_6^9 = 0,1088 + 0,05 \cdot 0,0048 = 0,109;$$

$$x_7^9 = 595,909 + 0,05 \cdot (-18,3314) = 594,9925;$$

$$x_8^9 = 0,0014 + 0,05 \cdot (-7,5541) = 0,0014;$$

$$x_9^9 = 0,1939 + 0,05 \cdot 0,0031 = 0,194.$$

Table 1

Initial data of the passive experiment results

No. experim.	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	Y
1	0,802	400	1532	729	200	0,1743	417	0,0016	0,2042	0,6154
2	0,827	439	1529	790	152	0,1312	657	0,0015	0,1882	0,5792
3	0,728	444	1528	704	105	0,1248	431	0,0010	0,2113	0,5905
4	0,802	480	1535	804	127	0,1139	543	0,0016	0,2172	0,6171
5	0,759	492	1531	657	204	0,1067	610	0,002	0,2056	0,5954
6	0,855	449	1529	904	149	0,0793	679	0,0013	0,1653	0,5104
7	0,871	451	1531	962	154	0,0905	692	0,0015	0,1879	0,6554
8	0,846	442	1530	849	156	0,0717	712	0,0014	0,1838	0,5601
9	0,857	450	1533	849	147	0,0741	708	0,0012	0,1819	0,6085
10	0,831	444	1535	849	150	0,1281	642	0,0014	0,1938	0,7122
Mean value	0,8184	449,545	1531,36	812	154,091	0,1088	595,909	0,0014	0,1939	-
11	0,82	450	1531	812	154	0,109	595	0,0014	0,194	0,8047

This experiment realization in production environment led to the result: $y_{11} = 0,804$ (80 %).

Similar values of the optimization criterion of input factors in experiments 10 – 11 show that the "nearly stationary area" is achieved [4].

Thus, on the average steel quality in the first nine experiments was 0,597 (59,7 %), and in the future (experiments 10 and 11) increased by nearly 30 %.

The algorithm of processing experiment results in order to obtain a linear model presents the following stages:

1. We count additional coefficients λ , A , C :

$$\lambda = \frac{kN}{(k+2)(N-n_0)} = \frac{9 \cdot 10}{(9+2)(10-1)} = 0,91; \quad (6)$$

$$A = \frac{1}{2\lambda[(k+2)\lambda - k]} = \frac{1}{2 \cdot 0,91[(9+2) \cdot 0,91 - 9]} = 0,55; \quad (7)$$

where k is the number of factors; N is the total number of experiments; n_0 is the number of experiments in the plan center (in the zero point).

$$C = \frac{N}{\sum_{i=1}^N x_{ij}^2}; \quad (8)$$

then $C_1 = 1,67$; $C_2 = 3,33$; $C_3 = 1,43$; $C_4 = 2,0$; $C_5 = 2,5$; $C_6 = 1,43$; $C_7 = 1,43$; $C_8 = 1,67$; $C_9 = 1,43$.

2. We define values S_0 , S_j , S_{jj} :

$$S_0 = \sum_{i=1}^N y_i = 60,44. \quad (9)$$

$$S_j = \sum_{i=1}^N x_{ij} y_i; \quad (10)$$

then $S_1 = 114,86$; $S_2 = 59,70$; $S_3 = -30,24$; $S_4 = -63,55$; $S_5 = 0,33$; $S_6 = -42,76$; $S_7 = 51,14$; $S_8 = 11,85$; $S_9 = 73,93$.

$$S_{jj} = \sum_{i=1}^N x_{ij}^2 y_i; \quad (11)$$

then $S_{11} = 352,02$; $S_{22} = 182,78$; $S_{33} = 417,79$; $S_{44} = 296,70$; $S_{55} = 241,83$; $S_{66} = 424,12$; $S_{77} = 415,73$; $S_{88} = 353,72$; $S_{99} = 409,73$.

3. We count the model coefficients:

$$b_0 = \frac{A}{N} \left[2\lambda^2(k+2)S_0 - 2\lambda C \sum_{j=1}^k S_{jj} \right] = \frac{0,55}{10} [2 \cdot 0,91^2 \cdot (9+2) \cdot 60,44 - 2 \cdot 0,91 \cdot 3094,43] = 60,44. \quad (12)$$

$$b_j = \frac{C}{N} S_j; \quad (13)$$

$$b_1 = \frac{C_1}{N} \cdot S_1 = \frac{1,67}{10} \cdot 114,87 = 19,14;$$

then $b_2 = 19,90$; $b_3 = -4,32$; $b_4 = -12,71$; $b_5 = 0,08$; $b_6 = -6,11$; $b_7 = 7,31$; $b_8 = 1,97$; $b_9 = 10,56$.

$$b_{jj} = \frac{A}{N} \left\{ C^2 [(k+2)\lambda - k] S_{jj} + C^2 (1-\lambda) \sum_{j=1}^k S_{jj} - 2\lambda C S_0 \right\}; \quad (14)$$

$$b_{11} = \frac{0,55}{10} \cdot \{1,67^2 [(9+2) \cdot 0,91 - 9] \cdot 352,02 + 1,67^2 \cdot 3094,43 - 2 \cdot 0,91 \cdot 1,67 \cdot 60,44\} = 86,69;$$

then $b_{22} = 1268,78$; $b_{33} = 491,89$; $b_{44} = 702,054$; $b_{55} = 912,9$; $b_{66} = 499,00$; $b_{77} = 489,58$; $b_{88} = 573,31$; $b_{99} = 482,85$.

4. We find the reproducibility dispersion of experiments $D(\bar{y})$:

$$D(\bar{y}) = \frac{1}{N-1} \sum_{i=1}^{n_0} (y_{i0} - \bar{y}_0)^2 = 29,14. \quad (15)$$

$$D_{b0} = 2A\lambda^2(k+2) \frac{D(\bar{y})}{N} = 2 \cdot 0,55 \cdot 0,91^2 (9+2) \cdot \frac{29,14}{10} = 29,14; \quad (16)$$

$$D_{bj} = \frac{C}{N} D(\bar{y}); \quad (17)$$

$$D_{b1} = \frac{C_1}{N} D(\bar{y}) = \frac{1,67}{10} 29,14 = 4,86;$$

then $D_{b2} = 9,71$; $D_{b3} = 4,16$; $D_{b4} = 5,83$; $D_{b5} = 7,28$; $D_{b6} = 4,16$; $D_{b7} = 4,16$; $D_{b8} = 4,86$; $D_{b9} = 4,16$.

$$D_{bij} = \frac{A}{N} [(k+1)\lambda - (k-1)] C^2 D(\bar{y}); \quad (18)$$

$$D_{b11} = \frac{0,55}{10} [(9+1) \cdot 0,91 - (9-1)] \cdot 1,67^2 \cdot 29,14 = 4,86;$$

then $D_{b22} = 19,43$; $D_{b33} = 0,59$; $D_{b44} = 2,33$; $D_{b55} = 1,56$; $D_{b66} = 1,71$; $D_{b77} = 0,89$; $D_{b88} = 0,69$; $D_{b99} = 0,51$.

5. We estimate the importance of the model coefficients by the condition:

$$\frac{|b_j|}{\sqrt{D_{bj}}} = t_j > t_{\text{tab}}, \quad (19)$$

where $|b_j|$ is the absolute value of j model coefficient; D_{bj} is the dispersion of j model coefficient; t_{tab} is the tabulated value of the Student's criterion with the given level of the value α and the number of the degree of freedom $\bar{m} = N - k^*$ [5], where k^* is the number of coefficients in the model, thence $t_{\text{tab}} = 2,26$.

Upon executing inequation (19), the considered model coefficient is significant, such ones were 6 coefficients: $t_1 = 8,69$; $t_2 = 6,39$; $t_4 = 5,26$; $t_6 = 2,99$; $t_7 = 3,58$; $t_9 = 5,18$.

As a result of calculations the following linear model was obtained:

$$Y = 60,44 + 19,14x_1 + 19,90x_2 - 12,71x_4 - 6,11x_6 + 7,31x_7 + 10,56x_9$$

3. Check the adequacy of the resulting model

We check out the model adequacy by the condition:

$$F = \frac{D_{ад}}{D(\bar{y})} < F_{tab}, \quad (20)$$

where F_{tab} is the tabulated value of the Fisher's criterion with the given level of significance α (0,05) [6] and the number of the degree of freedom (1):

$$F = \frac{83,60}{29,13} = 2,87 < F_{tab} = 3,63.$$

$D_{ад}$ is the adequacy dispersion (residual dispersion) [7]:

$$D_{ад} = \frac{1}{m} \left[\sum_{i=1}^N (y_i - \hat{y}_i)^2 - D(\bar{y}) \right] = 83,60. \quad (21)$$

Conclusions

Upon executing inequation (20), the model is considered adequate for the experimental data, and the task is considered to be solved.

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Thus, the found linear model accurately reflects the experimental data and can be used to analyze the object work and optimization.

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ПРИМЕНЕНИЕ ОРС ТЕХНОЛОГИИ В СИСТЕМАХ ДИСПЕТЧЕРИЗАЦИИ УЗЛОВ УЧЕТА ТЕПЛОВОЙ ЭНЕРГИИ

Приводится описание технологии построения системы диспетчеризации узлов учета тепловой энергии. Показана реализация системы диспетчеризации узлов учета тепловой энергии для систем теплоснабжения, а также показан пример элементов пользовательского интерфейса данной системы. Сделан вывод о возможности использования ОРС технологии при построении систем диспетчеризации узлов учета тепловой энергии.

Теплоснабжение, диспетчеризация и учет, энергоэффективность, ОРС.

The article describes techniques for constructing heat energy metering system. The implementation of the heat energy metering stations for dispatching heating systems, as well as an example of the user interface elements of the system are shown. Analysis of the possibility to use OPC technology in the construction of dispatching systems of heat energy metering stations is provided.

Heating system, data acquisition, energy efficiency, OPC.

Введение

Одна из характерных тенденций последних лет в сфере приборного учета тепла – это неуклонное повышение интереса к технологиям удаленного сбора данных и системам диспетчеризации. Они позволяют отказаться от ручных методов съема информации и повысить надежность и оперативность управления сетями централизованного теплоснабжения [2].

С развитием коммерческого учета тепла задача оперативного и своевременного сбора данных с теплосчетчиков приобретает все большую актуальность. Подключение ЦТП и ИТП к сетям сбора данных облегчает контроль и управление оборудованием, упо-

рошает ведение расчетов за теплоэнергию, как с предприятиями, так и с управляющими компаниями и ТСЖ [3].

Еще одно преимущество состоит в возможности анализировать работу тепловых пунктов и своевременно реагировать на возникшие проблемы. Имея точную информацию о параметрах работы системы теплоснабжения, можно решать любые спорные вопросы между поставщиком и потребителем тепловой энергии. Абонент тем самым защищает себя от возможных необоснованных исков. Но реализации таких решений часто препятствует необходимость немалых капиталовложений. Однако в конечном итоге