Selection of the Cutting Conditions Considering Quality of Chip Disposal

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The quality of chip disposal which can be given by merit marks of chip forms is estimated considering cutting conditions and work materials. The merit marks are expressed as a mathematical model identified by GMDH (Group Method of Data Handling) algorithm with successive determination of polynomial trends containing interaction terms. The established model can be used as a constraint in determining economically optimum cutting condition, that is, it can be selected under high quality of chip disposal.

1. Introduction

The mathematical models expressing quality of chip disposal by means of merit marks of chip forms are identified by basic GMDH[1)] and GMDH of variable selection type[2)]. In those models, merit marks are output variables and chemical compositions and mechanical properties of work materials are input variables under constant cutting conditions. The factors affecting to the chip forms are selected from among the chemical compositions and mechanical properties and then the relationship between each factor and the chip forms is investigated.

This paper describes identification of a mathematical model by GMDH algorithm, considering the factors (cutting speed, feed, depth of cut, nose radius and side cutting edge angle in addition to the characteristics of work materials) and their interactions. Since GMDH algorithm with successive determination of polynomial trends proposed by Ivakhnenko[3)] is the way to introduce one variable at each layer, the algorithm cannot be applied to identify the systems containing interactions between input variables. In this paper a new GMDH algorithm with successive determination of trends containing interaction terms is presented. The identified model by the proposed algorithm can be used for one of constraints in determination of economically optimum cutting conditions for a given work material.

2. GMDH Algorithm with Successive Determination of Polynomial Trends Containing Interaction Terms

Let us describe the GMDH algorithm that uses the partial descriptions with all inputs taken not only one variable but also two variables at a time to consider interactions among input variables.

Step (1). Choose the input variables considered to affect the output.

Step (2). Separate the data into a training set and a checking set.

The training data are used to estimate the coefficients of the partial descriptions.

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The checking data are used to evaluate the accuracy of the partial descriptions and to prevent overfitting. The following method of separation[4] is used:

Calculate the variance of all variables

$$D_i^2 = \sum_{j=1}^{p} \left(\frac{x_{ij} - \overline{x}_j}{\sigma_j} \right)^2 \tag{1a}$$

$$\sigma_j^2 = \frac{1}{n} \sum_{i=1}^{n} (x_{ij} - \overline{x}_j)^2 \tag{1b}$$

where p is the number of input variables and n is the number of data. Arrange the data points sorted in descending order of magnitude. Roughly 50 ~ 70% of the data with larger variance are put into a training set, and the rest, 30 ~ 50% of the data, with smaller variance are put into a checking set.

Step (3). Form the partial descriptions as follows:

(1) The partial descriptions with all inputs taken one variable.

Estimate the coefficients of

$$y_{i1} = f_{i1}(x_i) = a_{01} + a_{11}x_i \tag{2}$$

$$y_{i2} = f_{i2}(x_i) = a_{02} + a_{12}x_i + a_{22}x_i^2 \tag{3}$$

The coefficients in eqs. (2) and (3) are estimated by the least squares method using the training data. Calculate the mean square error between each estimated value and the checking data

$$\Delta_m^2 = \frac{1}{n_{ch}} \Sigma_{n_{ch}} (\hat{y}_{im} - y_i)^2 \quad m = 1.2 \tag{4}$$

where n_{ch} is the number of checking data. The $\hat{y}_{im}$ are then sorted according to these values. Select m_{opt} that minimizes the mean square error:

$$\hat{y}_i = f_i(x_i) = f_{im_{\mathrm{opt}}}(x_i) \tag{5}$$

$$\Delta_i^2 = \Delta_{im_{\mathrm{opt}}}^2 \tag{6}$$

Choose $f_i(x_i)$ and Δ_i^2, varying the argument number i $(i = 1, \cdots, p)$.

(2) The partial descriptions with all inputs taken two variables at a time.

Form the combination with all inputs taken two variables at a time:

$$C_k = (x_i, x_j) \tag{7}$$

Estimate the coefficients of

$$\hat{y}_{k1} = g_{k1}(x_i, x_j) = b_{01} + b_{11}x_i + b_{21}x_j + b_{31}x_ix_j \tag{8}$$

$$\hat{y}_{k2} = g_{k2}(x_i, x_j) = b_{02} + b_{12}x_i + b_{22}x_j + b_{32}x_ix_j + b_{42}x_i^2 \tag{9}$$

$$\hat{y}_{k3} = g_{k3}(x_i, x_j) = b_{03} + b_{13}x_i + b_{23}x_j + b_{33}x_ix_j + b_{53}x_j^2 \tag{10}$$

$$\hat{y}_{k4} = g_{k4}(x_i, x_j) = b_{04} + b_{14}x_i + b_{24}x_j + b_{34}x_ix_j + b_{44}x_i^2 + b_{54}x_j^2 \tag{11}$$

Calculate the mean square error between each estimated value and checking data as

$$\delta_m^2 = \frac{1}{n_{ch}} \Sigma_{n_{ch}} (\hat{y}_{km} - y_i)^2 \qquad m = 1, \cdots, 4 \tag{12}$$

Select m_{opt} that minimizes the mean square error:

$$\hat{y}_k = g_k(x_i, x_j) = g_{km_{\text{opt}}}(x_i, x_j) \tag{13}$$

$$\delta_k^2 = \delta_{km_{\text{opt}}}^2 \tag{14}$$

Choose $g_k(x_i, x_j)$ and δ_k^2, varying the argument number k ($k = 1, \cdots, s$), where $s = {}_pC_2$.

Step (4). Select the optimum partial descriptions.

As the optimum partial descriptions, select F partial descriptions in ascending order of errors among Δ_i^2 ($i = 1, \cdots, p$) and δ_k^2 ($k = 1, \cdots, s$) where F denotes a freedom of choice. To illustrate, let $F = 3$ and minimum errors by Δ_1^2, Δ_2^2 and δ_k^2, as shown in Fig. 1. The partial descriptions for the first layer are as follows:

$$\begin{aligned} \hat{y}_1 &= f_1(x_1) \\ \hat{y}_2 &= f_2(x_2) \\ \hat{y}_3 &= g_k(x_i, x_j) \end{aligned} \tag{15}$$

Step (5). The second layer.

In the second layer, the residuals, $z_1 = y - f_1(x_1)$, $z_2 = y - f_2(x_2)$ and $z_3 = y - g_k(x_i, x_j)$ become new output variables respectively. Form the partial descriptions using the remaining $p + s - 1$ variables with Step (3). The partial descriptions for the second layer are as follows:

$$\text{group 1} \left\{ \begin{aligned} y - f_1(x_1) &= f_{12}(x_2) \\ y - f_1(x_1) &= f_{13}(x_3) \\ &\vdots \\ y - f_1(x_1) &= g_{1k}(x_i, x_j) \end{aligned} \right.$$

$$\text{group 2} \left\{ \begin{aligned} y - f_2(x_2) &= f_{21}(x_1) \\ y - f_2(x_2) &= f_{23}(x_3) \\ &\vdots \\ y - f_2(x_2) &= g_{2k}(x_i, x_j) \end{aligned} \right. \tag{16}$$

$$\text{group 3}\left\{\begin{array}{l} y-g_k(x_i,x_j)=f_{31}(x_1) \\ y-g_k(x_i,x_j)=f_{32}(x_2) \\ \quad\vdots \qquad\qquad\qquad \vdots \\ y-g_k(x_i,x_j)=g_{3s}(x_{p-1},x_p) \end{array}\right.$$

Select the group containing the polynomial that minimizes the error among these $3X(p+s-1)$ polynomials. In this layer the most effective variable in the first layer among them is selected. To illustrate, let Δ^2_{24} be the minimum error as shown in Fig. 1. Then the variable to be introduced in the first layer becomes x_2 and the partial description for the first layer becomes $f_2(x_2)$. In the second layer, select $F(F=3)$ partial descriptions in ascending order of errors are selected again, and then those are let through to the third layer, etc.

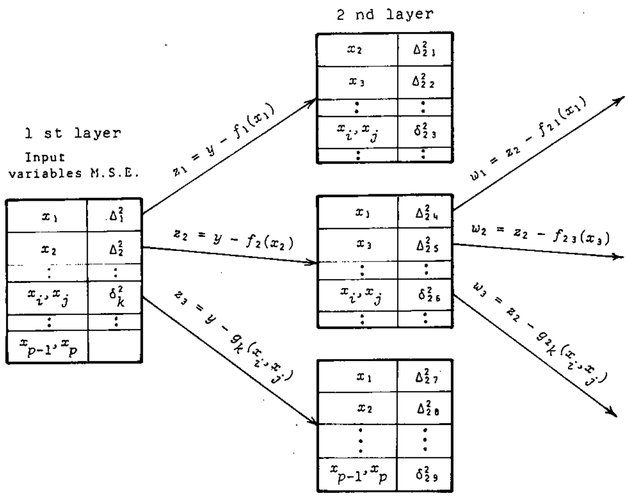


Fig. 1. Structure of GMDH algorithm $F = 3$

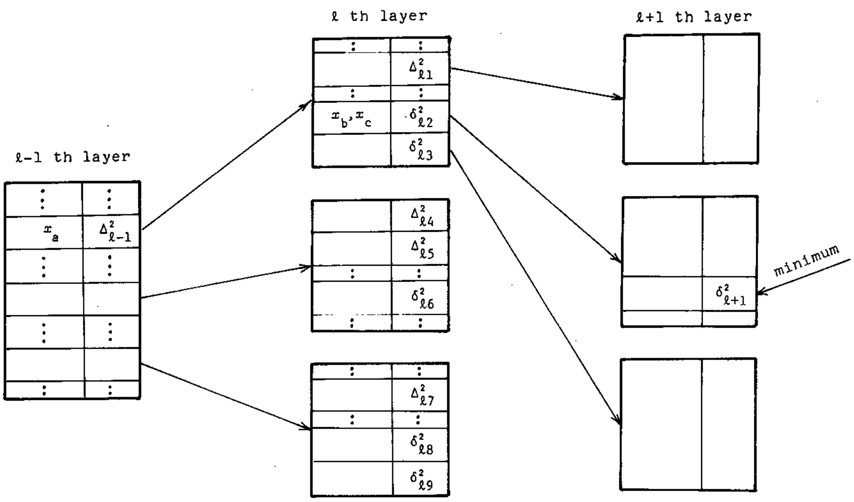


Fig. 1. (Continued)

Step (6). Stopping rule.

To illustrate, let the minimum error of the lth layer be Δ_{l1}^2 and $\Delta_{l-1}^2 \geqslant \Delta_{l1}^2$ as shown in Fig. 1 (Continued). Then the variable to be introduced in the $(l-1)$th layer becomes x_a. Furthermore let the minimum error of the $(l+1)$th layer be δ_{l+1}^2. Then the variables to be introduced in the lth layer are x_b and x_c. If $\Delta_{l-1}^2 < \Delta_{l1}^2$, then this procedure stops up to the $(l-1)$th layer. Consequently the obtained complete description is

$$y = f_2(x_2) + g_2(x_d, x_e) + g_3(x_f, x_g) + \cdots + f_{l-1}(x_a) \tag{17}$$

3. Identification of Chip Form Prediction Model by GMDH

The prediction model for chip forms in turning is identified by GMDH algorithm with successive determination of trends containing interaction terms. In the model the characteristics of work materials in Table 1 and the cutting conditions in Table 2 are input variables, and in which the merit marks for chip forms based on INFOS data sheet in Fig. 2 are output variables. The procedure of the identification is as follows:

(1) Selection of input variables

Cutting speed V, feed f, depth of cut d, nose radius R and side cutting edge angle C_s concerned with cutting conditions, and carbon C, sulphur S, chromium C_r, elongation El, reduction of area $R.A.$ and Brinell hardness H_B concerned with work materials[1] are selected as input variables.

(2) Separation of input and output data

The variances of input data are calculated by eq. (1) and the data with larger variances are put into the training set and the rest are put into the checking set. The separation ratios are made changeable so as to obtain the optimum model.

(3) Generation and selection of partial descriptions

By eqs. (2) and (3) for x_i $(i = 1, \cdots, 9)$ and eqs. (8), (9), (10) and (11) for C_k (x_i, x_j) $(k = 1, \cdots, 55)$, total 64 partial descriptions are generated. The parameters of these descriptions are estimated by the least square method using the training data, and Δ^2 in eq. (4) and δ^2 in eq. (12) are calculated using the checking data. The five $(F = 5)$ mean square errors in increasing order are determined and the corresponding five descriptions are selected.

Step (5) is to be repeated on and after the second layer, and the operation is terminated by the stopping rule in Step (6).

As the results of varying the separation ratio (N_t/N_c), the introduced variables and the mean square errors at each layer are obtained as shown in Table 3. It is evident from the table that the model corresponding to $N_t/N_c = 25/13$ is adopted as the optimum and that variable numbers 2, 5, 6, 7 and 9 have great effect on the chip forms.

The complete description is expressed as sum of partial descriptions (see Appendix) and the estimate of the merit mark of chip form can be obtained by substituting the data into these descriptions. The contours of the merit marks P are shown in Fig. 3 for a given work material and tool geometry.

Thus the chip forms can be predicted with the model identification using the pro-

Table 1. Chemical compositions and mechanical properties of work materials.

Work material	Chemical compositions (%)									Mechanical properties				
	C	Si	Mn	P	S	Ni	Cr	Pb	The others	Yield point (Y.P.) (kg/mm^2)	Tensile stress (T.S.) (kg/mm^2)	Elongation (El) (%)	Reduction of area (R.A.) (%)	Brinell hardness (H_B)
S15C	0.16	0.32	0.44	0.013	0.022	0.01	0.02	–	–	30.1	42.1	42.0	68.2	112
S25C	0.23	0.31	0.39	0.025	0.021	0.02	0.02	–	–	31.2	46.9	37.5	62.3	127
S35C	0.31	0.29	0.68	0.012	0.015	0.02	0.09	–	–	32.6	56.1	32.0	54.0	150
S45C	0.49	0.29	0.72	0.015	0.007	0.02	0.09	–	–	40.8	69.0	28.0	49.5	189
S55C	0.55	0.28	0.70	0.013	0.020	0.03	0.08	–	–	38.5	73.0	25.5	41.6	203
S43C-Pb	0.42	0.29	0.74	0.023	0.018	0.03	0.10	0.16	–	35.1	65.5	28.0	47.9	177
S50C-S	0.50	0.27	0.67	0.022	0.053	0.02	0.10	–	–	38.7	66.2	27.5	43.7	183
S43C-Ca-S-Pb	0.44	0.28	0.79	0.020	0.065	<0.01	0.10	0.14	Ca 0.0002	32.8	66.4	26.5	43.7	178
SCM22	0.19	0.38	0.72	0.022	0.016	0.02	1.03	–	Mo 0.20	35.1	52.8	36.0	68.2	155
SCM3	0.35	0.33	0.75	0.021	0.013	0.02	1.07	–	Mo 0.18	69.4	96.8	18.5	47.4	264

Table 2. Experimental conditions and the results

Trial Number	Cutting speed V m/min	Feed f mm/rev.	Depth of cut d mm	Nose radius R mm	Side cuttg. edge angle C_s degree	Work material	Merit mark of chip form P
1	230	0.5	2.1	1.6	15	S55C	7.83
2	130	0.3	1.3	0.8	15	S43C-Pb	8.63
3	280	0.4	1.7	1.2	30	S50C-S	2.88
4	180	0.6	1.7	1.2	30	S50C-S	8.23
5	230	0.3	1.3	0.8	15	S25C	9.38
6	130	0.5	2.1	1.6	15	S45C	8.00
7	80	0.4	1.7	1.2	30	S35C	8.70
8	180	0.2	1.7	1.2	30	S35C	1.88
9	180	0.4	1.7	1.2	30	S43C-Ca-S-Pb	7.11
10	180	0.4	1.7	1.2	30	S15C	8.95
11	280	0.4	1.7	1.2	30	S35C	8.63
12	80	0.4	1.7	1.2	30	S50C-S	4.88
13	180	0.6	1.7	1.2	30	S35C	9.00
14	180	0.2	1.7	1.2	30	S50C-S	2.00
15	180	0.4	1.7	1.2	30	S50C-S	5.75
16	180	0.4	1.7	1.2	30	S35C	8.25
17	180	0.4	1.7	1.2	30	S55C	3.88
18	180	0.4	1.7	1.2	30	S45C	3.13
19	130	0.1	0.8	0.8	15	S35C	1.90
20	130	0.15	1.8	1.6	15	S45C	1.80
21	150	0.6	1.0	1.6	45	S35C	9.28
22	110	0.4	2.0	0.8	45	S55C	1.80
23	230	0.5	2.0	1.6	15	S25C	7.10
24	230	0.5	1.2	0.8	15	S45C	7.25
25	250	0.125	2.2	0.8	45	S25C	4.00
26	210	0.125	1.0	1.6	45	S55C	2.20
27	280	0.2	1.3	1.2	30	S43C-Ca-S-Pb	5.00
28	80	0.175	1.5	1.2	30	S50C-S	2.00
29	180	0.7	1.3	1.2	30	S43C-Pb	9.00
30	200	0.06	1.3	1.2	30	S50C-S	1.00
31	170	0.175	2.5	1.2	30	SCM22	1.70
32	200	0.3	0.5	1.2	30	S43C-Ca-S-Pb	4.36
33	160	0.25	1.5	2.0	30	SCM22	1.48
34	160	0.2	1.7	0.4	30	S43C-Pb	3.90
35	170	0.3	1.2	1.2	60	S43C-Pb	7.00
36	190	0.35	1.2	1.2	0	S43C-Ca-S-Pb	5.44
37	180	0.25	1.2	1.2	30	SCM3	3.00
38	190	0.35	1.2	1.2	30	S15C	8.90

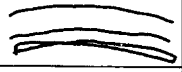
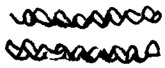
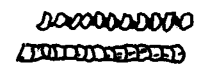
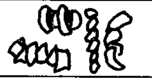
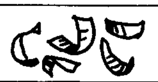
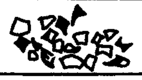
Merit marks	Chip forms	
1		Ribbon chips
2		Irregular chips
3		Flat helix
4		Beveled helix
5		Long cylindrical helix
6		Short cylindrical helix
7		Spiral helix
8		Spiral chips
9		Roll chips
10		Powder

Fig. 2.
Classification of chip forms

posed GMDH algorithm and hence work material or cutting condition can be selected to obtain high quality of chip disposal. Accordingly the model can be used as a constraint in determining economically optimum cutting conditions.

4. Conclusion

(1) GMDH algorithm with successive determination of trends containing interaction terms is proposed and the identification method of a low degree mathematical model considering various input variables is shown.

(2) Using the proposed algorithm, prediction model for chip forms in which cutting conditions, tool geometry and characteristics of work materials are independent variables can be obtained.

(3) The established model can be used as a constraint in determining economically optimum cutting conditions.

Table 3. Introduced variables and mean square error

	N_t/N_c	19/19		20/18		21/17		22/16		23/15		24/14		25/13		26/12		27/11	
	1	2	9	2	6	2	6	2	6	2	6	2	6	2	6	2	6	2	6
	2	6	9	6	9	4	5	9	11	4	5	5	7	5	7	5	7	5	7
	3	5	6	5	6	9	11	4	5	9	11	6	9	6	7	6	7	6	7
	4	9	10	9	10	5	7	5	7	5	7	5	10	6	8	6	8	6	8
	5	4	5	4	5	5	8	7	10	5	11	4	5	5	11	5	11	5	9
	6	10		2		2	8	5	8	3	7	5	8	4	7	4	5	4	5
	7	5		5		7	10	10		3	8	1	5	4	5	4	7	4	7
	8	8	10	8	10	7	9	7		7	9	1	2	4		7	8	2	7
	9	5	10	8		5	10	5	9	5	9	5		5	8	5	8	5	
	10	8		10		3	10	3	8	3		2	4	3	4	5		2	4
	11					3	8	2	3	5		4	8	3	8	4		5	11
	12					2	3	2	8	11		4	7	7	8	3	4	4	
	13					10		8		9		2	3	7		3	8	11	
	14					8		9				3	4	1	5	7		7	
	15					3		2				7	9	2	3	8		2	
	16					3	5	7	9			5	11	3	7			2	5
	17					5	9					4	6	1	2			1	5
Layers	18					3	4					2	8	2	4			1	2
	19					9						3	7	4	6			2	3
	20					4	8					4	10	2	8			4	6
	21					4						7		4	8			3	8
	22					5						1	8	2	5			2	11
	23											2	10	1				4	10
	24											7	8	8	11			8	11
	25											4		4	10			2	9
	26											9		8	9			4	9
	27											1		4	11			1	8
	28											8		2	11			2	10
	29													4	9			8	9
	30													1	8			7	10
	31													2				3	4
	32													8				9	
	33													3				3	
	34																	4	8
	35																	8	
	MSE	1.54265		1.58017		1.26467		1.28639		1.40658		1.09965		1.06045		1.34982		1.07907	

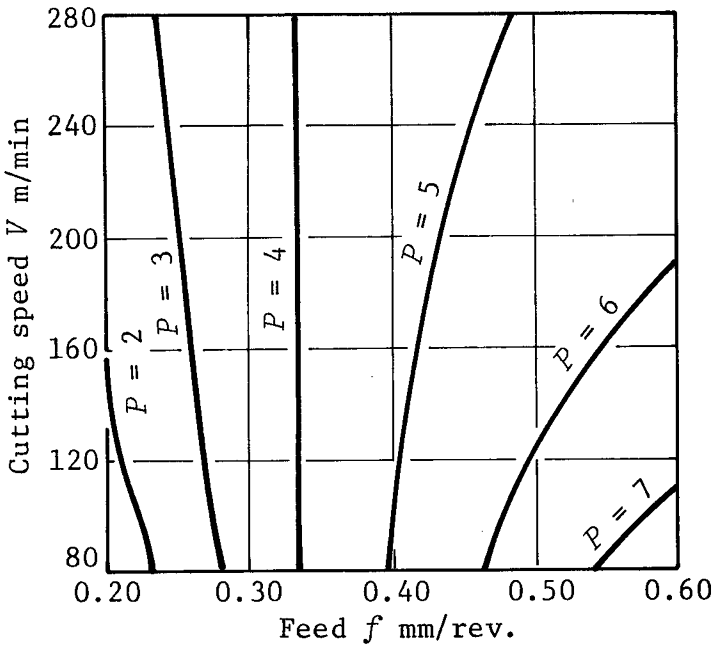


Fig. 3. The contours of merit marks in chip forms

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4) A.G. Ivakhnenko and Yu.V. Koppa, Soviet Automatic Control, 3, 28 (1970).

APPENDIX

The partial descriptions and their parameters of the optimum model in section 3 is shown in order of the selection layer as in Table A-1. In the table, for example, the partial description in the first layer is

$$P = -3.06 + 29.8x_1 + 16.4x_2 - 19.7x_1x_2 - 11.2x_1^2 - 22.4x_2^2$$

The complete description is expressed as sum of all of the partial descriptions.

Table A-1. The input variables and parameters in partial descriptions for each layer

Layers	$f(x_i, x_j)$	x_0	x_i	x_j	$x_i x_j$	x_i^2	x_j^2
1	x_2, x_6	−3.062	29.77	16.42	−19.72	−11.17	−22.44
2	x_5, x_7	3.526	−0.310	42.89	3.191	0.004	−1588
3	x_6, x_7	−13.17	36.03	602.3	−1040	−21.68	−1730
4	x_6, x_8	0.661	−4.048	10.71	9.360		−12.83
5	x_5, x_{11}	−36.50	1.293	7.091	−0.251		
6	x_4, x_7	−0.621	0.145	68.03	−22.51		−607.9
7	x_4, x_5	4.422	−3.487	−0.158	0.126		
8	x_4	0.000	0.000				
9	x_5, x_8	−0.394	0.017	4.662	−0.207		1.350
10	x_3, x_4	0.080	−0.056	−0.748	0.478		
11	x_3, x_8	0.476	−0.262	−2.892	1.467		
12	x_7, x_8	−0.399	22.12	2.930	−191.4		
13	x_7	0.000	0.000				
14	x_1, x_5	10.59	−2.066	−0.397	0.078		
15	x_2, x_3	1.072	−4.337	−0.624	2.525		
16	x_3, x_7	−0.160	0.078	6.170	−2.624		−23.03
17	x_1, x_2	−11.74	2.278	36.78	−7.153		
18	x_2, x_4	−2.198	7.242	1.764	−5.632		
19	x_4, x_6	5.285	−5.692	−11.19	9.507	0.937	
20	x_2, x_8	−0.303	0.713	0.142	1.196		
21	x_4, x_8	0.393	−0.328	−0.773	0.588		
22	x_2, x_5	−0.368	2.518	0.003	−0.015	−3.057	
23	x_1	0.668	−0.131				
24	x_8, x_{11}	3.828	3.044	−0.869	1.094	−7.775	
25	x_4, x_{10}	−18.36	14.27	4.727	−3.790	0.346	
26	x_8, x_9	96.52	7.781	−57.96	1.537	−11.96	8.598
27	x_4, x_{11}	12.94	−6.737	−3.566	1.215	0.186	0.215
28	x_2, x_{11}	−6.484	19.98	1.214	−3.641	−1.322	
29	x_4, x_9	−5.156	3.671	1.649	−1.290	0.263	
30	x_1, x_8	−1.312	0.249	12.11	−2.333		
31	x_2	−0.066	0.217				
32	x_8	−0.004	0.021				
33	x_3	0.027	−0.017				