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Comparisons of Random Forest and Support Vector Machine for Predicting Blasting Vibration Characteristic Parameters

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Abstract

The prediction of blasting vibration characteristic parameters is very important to evaluate the situations of blasting vibration damage. Blasting vibration of rock mass is affected by lots of characteristics, such as charging parameter, rock type and geological topography. The characteristics should be comprehensively considered in order to accurately predict the blasting vibration. Based on training and testing 93 sets of measured data in an open-pit mine, Support Vector Machine (SVM) and Random Forest (RF) methods are applied to predict the peak particle velocity (PPV), first dominant frequency and duration time of first dominant frequency of blasting vibration. The other 15 groups of measured data are tested as forecast samples, of which the predicted results are consistent with the measured ones. Results show that the prediction accuracies of SVM and RF models were acceptable. The average error rate of SVM is lower than results using RF, and the weight of factors is determined using RF. It is a new approach to predict destructive effect on housing under blasting vibration using SVM and RF, which can be applied to practical engineering.

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Keywords: blasting engineering; SVM; RF; PPV; first dominant frequency; duration time first dominant frequency

1. Introduction

The blasting is a main means to excavate soil and rock in mining, transportation and hydroelectric projects. It will cause vibration which may be a hazard to the nearby buildings. How to accurately analyze and predict the rules of peak particle velocity (PPV), and then optimize the blasting design and construction, is a main method to decrease the damage caused by blasting vibration. At present, the prediction of the blasting vibration is widely calculated using regression analysis by Sadaovsk formula

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according to monitoring data. The vibration velocity then could be predicted based on the regressed formula [1~2]. However, only two factors, charging amount and explosive distance, are taken into account in the formula. Thus usually it can not provide considerable accuracy in predicting vibration velocity. Because blasting vibration is not only affected by blasting parameters such as charging amount, delay time, explosive distance, but has something to do with geological conditions like elevation difference caused by geological topography, rock properties and structure of rock mass, etc[3~4]. There is a complicated nonlinear relationship between blasting vibration and these parameters, so it is difficult to utilize one empirical equation to embrace all these factors.

The methods to prediction on blasting vibration are of two types. One begins with forecasting blasting vibration characteristics such as amplitude, main frequency and duration time. Then safety status of construction can be judged by blasting vibration safety criteria and blasting vibration can be controlled at the end. This is the main method applied by most researchers. The other one predicts safety status of construction directly according to blasting parameters, site conditions, features of protected constructions and expert's knowledge. Both methods require large amount of test data.

The empirical formula adopted in the first method to predict vibration magnitude is called Sadaovsk formula and its transformed formula. Through a great deal of practical monitoring and by regression analysis method to attain values of empirical factors, it aims to predict the PPV caused by blasting vibration. Due to too many factors affecting blasting vibration, the first method provides a poor accuracy in prediction. Lately, a number of researchers applied neural network model to predict vibration velocity and it achieved a good result. In Papers [5~7], charge amount and explosive distance are regarded as input data in a neural network model to predict the blasting vibration. The result shows that network prediction has a high accuracy than empirical formula prediction. In Ref [8], charge amount, explosive distance and elevation are regarded as input data and fuzzy neural network model is established. The model predicts blasting vibration in HeShan iron mine, with an average error of 5.58% to the actual value. In paper [9], maximum charge amount at one time, total charge amount, delay time, explosive distance, elevation, duration time are regarded as input data and BP neural network model is established. Comparing the empirical data and the predicted data, it is showed that the predicted data is closer to actual data. In paper [10], diameters of blast hole, numbers of blast hole, horizontal and vertical explosive distance are regarded as input data and BP neural network is established. With predicting the PPV on the ground, it proves that it has a more accuracy than traditional regression statistics.

Besides the blasting conditions, the second method refers to many other affected factors like protected target, and involves more uncertainties. Based on rough neural network, Shi [12] established a predicting model to housing under blasting vibration. Dong [13] used Fisher discriminative models to predict surface mining vibration damage to masonry structure. Both of them achieved a good application.

It is inevitable to eliminate the negative sides caused by blasting vibration. Before blasting much importance should be attached to predict blasting vibration and measures should be taken to protect the relevant target. In most cases, the protected target is close to blasting source, so more accuracy of blasting vibration at close range is needed. It asks us to put forward a more creative and effective method to predict blasting vibration. The method should have more predicting accuracy, reflect the fact affected by various factors and predict main frequency and duration time of blasting vibration. Support Vector Machine(SVM) and Random Forest(RF) were advanced and effective method for predictions. The paper takes blasting vibration on a practical copper mine for example. SVM and RF were used to predict blasting characteristics, and the predicted results were compared and analyzed.

2. Methodologies

2.1 Review of SVM

Support vector machine (SVM) is a new study method based on statistics theory. It is a machine learning theory frame and general way, established on a set of finite samples. Practical problems such as small sample, nonlinear analysis, local minimum points, can be solved by SVM. The basic conception is that through some pre-selected nonlinear reflection input data is reflected into a high dimensioned space in which the optimal classification hyper-plane is formed [13].

As to function fitting problems of SVM, it is actually a problem to fit data $\{x_i, y_i\}$, (i=1,2,…,n), $x_i \in R^n$ $y_i \in R$ with function $f(x) = w \bullet x + b$. So according to SVM theory fitting problems function is given as

$$f(x) = w \cdot x + b = \sum_{i=1}^{k} (a_i - a_i^*) K(xx_i) + b \tag{1}$$

Where, a_i, a_i^*, b are obtained through solving subsequent second optimization problems. Usually a small fraction of a_i, a_i^* is not zero, which is called support vector.

Max：

$$\begin{aligned} w(a, a^*) &= -\frac{1}{2} \sum_{i,j=1}^{k} (a_i - a_i^*)(a_j - a_j^*) K(x_i x_j) \\ &+ \sum_{i=1}^{k} y_i (a_i - a_i^*) - \varepsilon \sum_{i=1}^{k} (a_i + a_i^*) \end{aligned} \tag{2}$$

$$\text{s.t.} \begin{cases} \sum_{i=1}^{k} (a_i - a_i^*) = 0 \\ 0 \le a_i, a_i^* \le C, (i = 1, 2, \cdots, k) \end{cases} \tag{3}$$

Where C is penalty factor, showing the penalty degree to samples of excessive error ε; $K(x_i x_j)$ is kernel function, solving calculation problems of high dimension skillfully with introducing kernel functions. Kernel functions at present are mainly:

(1) Linear kernel :

$$K(x, y) = x \bullet y \tag{4}$$

(2) Polynomial kernel:

$$K(x, y) = [(x \bullet y) + 1]^d \qquad (d = 1, 2, \cdots) \tag{5}$$

(3) Radial primary kernel function:

$$K(x, y) = \exp[\frac{-\|x - y\|^2}{\sigma^2}] \tag{6}$$

(4) Two layer neural kernel:

$$K(x, y) = \tanh[a(x \bullet y) - \delta] \tag{7}$$

2.2 Review of RF for regression [15]

Random forests for regression are formed by growing trees depending on a random vector Θ such that the tree predictor h($\mathbf{x}, \Theta$) takes on numerical values as opposed to class labels. The output values are numerical and we assume that the training set is independently drawn from the distribution of the random vector Y,**X**. The mean-squared generalization error for any numerical predictor h(**x**) is

$$E_{X,Y}(Y-h(X))^2 \tag{8}$$

The random forest predictor is formed by taking the average over k of the trees {h(**x**, Θ_k)}.Similarly to the classification case, the following holds:

Theorem 1. *As the number of trees in the forest goes to infinity*, *almost surrely*,

$$E_{X,Y}(Y-a\ v_k h(X,\Theta_k))^2 \to E_{X,Y}\left(Y-E_\Theta h(X,\Theta_k))^2\right). \tag{9}$$

Proof: see Appendix I in Ref[15].

Denote the right hand side of (12) as PE^* (forest)—the generalization error of the forest. Define the average generalization error of a tree as:

$$\mathrm{PE}^*\left(tree\right)=E_\Theta E_{X,Y}\left(Y-h\left(X,\Theta\right)\right)^2$$

Theorem 2. Assume that for all Θ , EY = E_X h(**X**, Θ). Then

$$\mathrm{PE}^*\left(forest\right)\le \mathrm{PE}^*\left(tree\right)$$

where ρ. is the weighted correlation between the residuals Y− h(**X**, Θ)and Y − h(X, Θ) where Θ,Θ' are independent.

Proof:

$$\mathrm{PE}^*\left(forst\right)=E_{X,Y}\left[E_\Theta\left(Y-h\left(X,\Theta\right)\right)\right]^2$$

$$=E_\Theta E_{\Theta'}E_{X,Y}\left(Y-h\left(X,\Theta\right)\right)\left(Y-h\left(X,\Theta'\right)\right) \tag{10}$$

The term on the right in (10) is a covariance and can be written as:

$$\overline{\rho}=E_\Theta E_{\Theta'}\left(\rho(\Theta,\Theta')\right)sd\left(\Theta\right)sd\left(\Theta'\right)/\left(E_\Theta sd\left(\Theta\right)\right)^2 \tag{11}$$

Then

$$\mathrm{PE}^*\left(forst\right)=\overline{\rho}\left(E_\Theta sd\left(\Theta\right)\right)^2\le\overline{\rho}\mathrm{PE}^*\left(tree\right)$$

Theorem (2) pinpoints the requirements for accurate regression forests—low correlation between residuals and low error trees. The random forest decreases the average error of the trees employed by the factor $\overline{\rho}$ The randomization employed needs to aim at low correlation.

3. SVM and RF models of blasting vibration characteristics prediction

3.1 Determination of model input factors

Excavation of rock mass by blasting comprises of two processes - releasing of explosive energy and movement of surrounding rock and soil. The effect on rock and soil can be regarded as wave mechanics process that can be treated as stress wave spreading in the medium and disturbing to the medium. After a comprehensive consideration, maximum amount of charge at one time (kg), total amount of charge(kg), horizontal distance(m), elevation difference(m), front row resistance line(m), presplit penetration ratio(%), integrity coefficient, angel of minimum resistance line to measured point, detonation velocity(m/s) are chosen as differentiating factors, presented as X_1(kg), X_2(kg), X_3 (m), X_4 (m), X_5(m), X_6（%）, X_7, X_8(°), X_9（m/s）, respectively. The characteristic parameters to predict blasting vibration are

PPV, first dominant frequency and first dominant frequency duration time, presented as Y_1(cm/s), Y_2 (Hz), Y_3 (ms) , respectively.

3.2 Determination of model

Input parameters should compromise all main factors affecting the blasting vibration. The input parameters are listed below: 1） charging amount at one time； 2) total charging amount; 3） horizontal distance; 4) elevation difference； 5) resistance line； 6) presplit blasting effect； 7) rock mass structure; 8) comparative distance between measured point and explosive region； 9) explosive type. The output parameters are PPV、 first dominant frequency and duration time first dominant frequency of blasting vibration. Structure of SVM and RF models is illustrated as Fig.1.

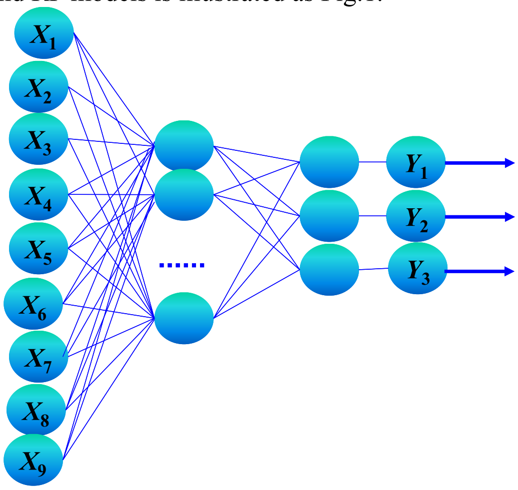

Fig.1 SVM and RF models for predicting blasting vibration characteristic parameters

4. Practical applications and discussions

The established SVM and RF models were applied to predict characteristic parameters of blasting vibration in a copper mine in China. 108 groups were achieved on the spot from Ref[12], of which 93 groups(see Appendix) were constructed as training sample model and the other 15 groups are used to inspect the rationality of testing model. Factors of testing samples include maximum amount of charge(kg), total amount of charge (kg), horizontal distance(m), elevation difference(m), front row resistance line(m), presplit penetration ratio(%), integrity coefficient, angel of minimum resistance line to measured point（°), and detonation velocity(m/s) , as listed in Table 1.

PPV, first dominant frequency and duration time of first dominant frequency were predicted by established models of SVM and RF, and the results were listed in Table 2. It can be seen from the table that the predicted value and measured value obtained from SVM and RF are of relative low comparative error. Comparative errors of SVM and RF were listed in Table 3. Results show that: except a few samples with high error, the majority comparative errors are within the reasonable range. The result proves that the established models were reasonable and reliable. To see the comparison more clearly, illustrate values of PPV, first dominant frequency and duration time of first dominant frequency , shown as Figs.2, 3, and 4. Weight parameters for all factors were listed in Table 3.

Table 1 Measured data of test model

NO.	X_1 (kg)	X_2 (kg)	X_3 (m)	X_4 (m)	X_5 (m)	X_6 （%）	X_7	X_8 (°)	X_9 （m/s)	Y_1 (cm/s)	Y_2 (Hz)	Y_3 (ms)
1	350	1050	114.7	16.8	5	80	0.38	160	2800	0.417	26.5	195
2	370	2150	70.3	42	7	0	0.73	180	4200	4.754	48.6	985
3	370	2150	101.2	54	7	0	0.56	115	4200	1.554	49.5	790
4	494	3952	122.6	62.1	5	0	0.32	120	2800	0.608	41.7	610
5	730	4380	115.7	50.9	6	50	0.42	180	4200	1.597	25.3	635
6	840	5660	214.7	75.1	6	0	0.52	120	4200	0.218	38.4	890
7	890	1800	72.1	42.0	5	100	0.73	80	4200	3.194	39.2	345
8	890	1800	53.2	30	5	100	0.65	50	4200	2.389	41.6	415
9	1090	5450	231.9	30.0	5	100	0.72	90	4200	0.496	27.8	650
10	1290	3870	177.6	73.0	6	0	0.56	180	4200	1.102	40.4	415
11	1410	6780	189.9	64.0	5	0	0.51	180	4200	1.047	38.3	985
12	1636	4980	125.1	42.2	4	0	0.55	180	4200	2.124	40.6	830
13	1790	5370	393.1	98.0	4	60	0.71	50	2800	0.302	16.2	505
14	1850	8500	68.5	30.0	6	0	0.50	180	2800	3.880	40.6	1380
15	2180	4360	226.9	106.0	5	0	0.46	60	4200	0.498	26.8	565

Table 2 The predicted results using SVM and RF

NO.	Results by SVM			Results by RF		
	Y_1 (cm/s)	Y_2 (Hz)	Y_3 (ms)	Y_1 (cm/s)	Y_2 (Hz)	Y_3 (ms)
1	0.74	23.9	406.84093	0.6896	34.46	412.52
2	3.2	45	1135.7527	1.8421	44	686.58
3	1.79	44.1	1034.607	1.4343	43.513	554.47
4	0.37	40.3	682.56488	0.7654	39.279	694.4
5	1.4	31.7	779.92653	1.4421	35.054	864.35
6	0.21	35.5	903.97768	0.9184	35.703	848.05
7	2.16	40	359.93863	1.8214	39.729	385.25
8	2.4	39.5	362.82871	1.7412	40.173	405.77
9	0.6	26.9	530.81646	0.5504	26.478	563.25
10	0.95	41	579.34102	0.9753	38.18	646.75
11	1.26	36.2	855.2419	1.1382	33.745	937.82
12	2.3	39.1	755.98129	1.4428	36.302	828.2
13	0.66	21	661.40232	0.5196	20.417	610.13
14	3.24	38.9	1242.3775	3.397	37.902	1180.1
15	0.94	27.3	613.2206	0.7617	28.778	625.22

Table 3 The difference errors of predicted results

NO.	RF Y_1 (%)	RF Y_2 (%)	RF Y_3 (%)	SVM Y_1 (%)	SVM Y_2 (%)	SVM Y_3 (%)
1	-0.65381	-0.30038	-1.11547	-0.77458	0.098113	-1.08636
2	0.612519	0.094643	0.302961	0.326883	0.074074	-0.15305
3	0.077031	0.120949	0.298143	-0.15187	0.109091	-0.30963
4	-0.25884	0.058058	-0.13836	0.391447	0.033573	-0.11896
5	0.096976	-0.38553	-0.36118	0.123356	-0.25296	-0.22823
6	-3.21272	0.070247	0.047135	0.036697	0.075521	-0.01571
7	0.429741	-0.01349	-0.11667	0.323732	-0.02041	-0.0433
8	0.271153	0.034303	0.022249	-0.0046	0.050481	0.125714
9	-0.10964	0.047542	0.133462	-0.20968	0.032374	0.183359
10	0.114997	0.054957	-0.55843	0.137931	-0.01485	-0.396
11	-0.08711	0.118921	0.047902	-0.20344	0.05483	0.131734
12	0.320723	0.105874	0.002169	-0.08286	0.036946	0.089179
13	-0.72057	-0.26032	-0.20818	-1.18543	-0.2963	-0.30971
14	0.124496	0.066458	0.144831	0.164948	0.041872	0.099726
15	-0.52952	-0.0738	-0.10658	-0.88755	-0.01866	-0.08535

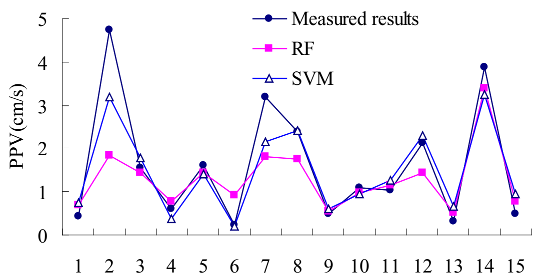

Fig.2 Comparison of measured and predicted data of PPV

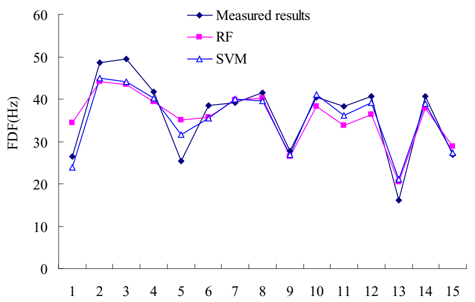

Fig.3 Comparison of measured value and predicted data of first dominant frequency(FDF)

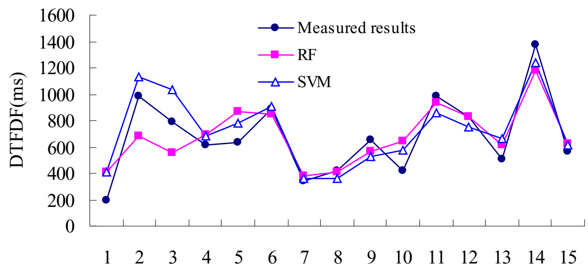

Fig.4 Comparison of measured and predicted data of duration time(DTFD)

Table 4 Weight parameters of RF model

Influenced factors	Weight parameters Y_1	Y_2	Y_3	Influenced factors	Weight parameters Y_1	Y_2	Y_3
X_1	4.9590	3.7934	3.6872	X_6	4.0503	3.127	3.3257
X_2	3.3465	4.5766	7.2648	X_7	4.0716	3.5561	3.0757
X_3	6.6132	6.6906	3.9349	X_8	2.6242	3.6809	3.8785
X_4	3.7361	4.1566	2.8287	X_9	2.3972	2.6542	2.9377
X_5	3.1226	3.9732	3.6174				

5. Conclusions

Nine discriminating factors are selected as influence factors. The predicted models for the blasting vibrations characteristics including PPV, first dominant frequency and duration time first dominant frequency are established based on the SVM and RF theory. The established models were applied to predict blasting vibration characteristics in a copper mine. 93 groups of measured data are trained and tested. The other 15 groups of measured data are tested as forecast samples. The study shows that the SVM and RF models have a low predicted error ratio. And the average predicted error ratio of SVM is lower than the results by RF. However, the RF can give the weight parameters of all factors, and the SVM has not this function. Therefore, the reasonable combination of SVM and RF to predict destructive effect on housing under blasting vibration is a scientific way, which can be applied to practical engineering.

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Appendix: 93 groups of samples from Ref[12].

Table Ⅰ 93 groups of samples

NO.	X_1 (kg)	X_2 (kg)	X_3 (m)	X_4 (m)	X_5 (m)	X_6 （%）	X_7	X_8 (°)	X_9 （m/s)	Y_1 (cm/s)	Y_2 (Hz)	Y_3 (ms)
1	160	1440	125.3	52.3	5	0	0.42	180	2800	0.343	42.3	395
2	312	3120	311.9	42	7	0	0.72	180	4200	0.753	32.9	860
3	312	3120	389.4	108	7	0	0.7	180	4200	0.572	25.3	810
4	312	3120	362.3	86	7	0	0.7	180	4200	1.214	27.8	1080
5	312	3120	199.2	30	7	0	0.73	180	4200	2.148	41.6	1110
6	350	1050	143.5	52.3	5	50	0.48	180	2800	0.609	25.6	210
7	400	3600	110.6	16.8	6	0	0.38	160	4200	0.898	41.5	1155
8	550	4400	89.5	42.0	5	90	0.73	180	2800	1.279	41	765
9	380	1550	162.4	73	4	90	0.3	40	2800	0.102	23.7	185
10	380	1550	147.8	62	4	90	0.35	60	2800	0.201	24.1	205
11	380	1550	104.9	28.6	4	90	0.41	60	2800	0.463	30.1	215
12	380	1550	336.2	58.9	5	80	0.48	55	2800	0.101	25.6	190
13	390	2730	120.9	46.9	4	100	0.3	40	2800	0.143	27.6	620
14	390	2730	69.9	53.9	6	100	0.65	180	4200	0.394	44.1	715
15	390	2730	50.4	30	6	100	0.65	180	4200	0.126	45.6	630
16	390	2730	137.8	63.1	5	80	0.51	55	2800	0.318	36.1	660
17	390	2730	63.3	27.6	5	80	0.53	55	2800	0.657	40.1	765
18	400	3600	47.1	16.9	6	0	0.41	160	4200	5.371	43.5	1225
19	400	3600	137.9	52.3	6	0	0.41	160	4200	0.815	41.8	1150
20	456	1860	284.1	85.3	6	0	0.52	180	2800	0.368	36	260
21	460	4600	443.6	108	7	0	0.75	180	2800	0.510	19.7	790
22	460	4600	363.3	42	7	0	0.75	180	2800	0.476	25.1	730
23	460	2760	323.6	30	6	0	0.65	150	2800	0.203	31.1	665
24	460	2760	313.2	86	6	0	0.65	150	2800	0.391	31.8	685
25	468	936	85.3	54	6	0	0.65	120	2800	2.486	51.1	165
26	468	936	75.5	30	6	0	0.78	180	2800	3.35	51.1	180
27	494	3952	66.7	28.6	5	0	0.55	180	2800	3.029	42.6	1020
28	494	3952	183.2	28.9	5	0	0.32	120	2800	0.105	39.1	680
29	494	1482	170.4	46.9	5	0	0.49	130	2800	0.195	42.7	155
30	494	1482	132.5	63.1	5	0	0.49	130	2800	0.413	46.2	165
31	494	5434	149.2	73.3	6	0	0.55	180	2800	0.923	44.9	1150
32	494	5434	96.4	27.6	6	0	0.58	180	2800	1.413	47.7	1260
33	494	1482	81.5	51.9	5	0	0.46	90	2800	0.806	48.6	285
34	494	1482	80.2	27.6	5	0	0.48	90	2800	0.598	48.4	285
35	507	7650	193.5	53	5	0	0.65	0	2800	0.106	40.8	1100

Continue Table Ⅰ 93 groups of samples

NO.	X_1 (kg)	X_2 (kg)	X_3 (m)	X_4 (m)	X_5 (m)	X_6 （%）	X_7	X_8 (°)	X_9 （m/s)	Y_1 (cm/s)	Y_2 (Hz)	Y_3 (ms)
36	507	7650	235.2	86	5	0	0.68	0	2800	0.196	25.6	1120
37	507	7650	332.3	86	5	0	0.75	40	2800	0.292	25.6	1385
38	532	6084	73	40	6	0	0.53	180	4200	2.372	48.2	1535
39	532	6084	124.2	73	6	0	0.51	180	4200	1.442	46.5	1125
40	550	4400	123.4	53.9	5	90	0.65	180	2800	1.562	37.6	785
41	550	4400	97.4	55.1	5	90	0.75	180	2800	1.425	39.6	750
42	646	8395	121.4	53	6	0	0.73	180	4200	3.55	45.1	1655
43	646	8395	121.7	53	6	0	0.65	150	4200	2.45	45	1550
44	646	1950	58.2	27.6	5	0	0.46	0	4200	1.4	49.6	350
45	646	1950	111.3	63.1	5	0	0.44	0	4200	0.347	46.6	325
46	730	4380	74.5	28.6	6	50	0.35	160	4200	1.912	29.6	815
47	770	3080	138.2	30	6	0	0.67	60	2800	1.365	43.7	725
48	770	3080	175.9	30	6	0	0.65	60	2800	0.243	41.8	650
49	770	3080	76.2	30	6	0	0.76	90	2800	4.631	48.9	885
50	840	5660	119.9	62.9	5	0	0.4	180	4200	1.809	38.9	1050
51	1160	4640	185.7	62.1	4	100	0.42	160	2800	0.108	20.6	680
52	890	1800	88.8	54	5	100	0.65	50	4200	2.542	39.8	310
53	890	1800	103.7	54	5	100	0.71	70	4200	2.316	38.6	310
54	1012	3036	92.3	42	4	0	0.63	0	2800	1.554	43.3	465
55	1012	3036	326.6	98	4	0	0.63	0	2800	0.160	23.5	385
56	1090	5450	391.5	86	5	100	0.65	90	4200	0.375	19.5	465
57	1090	5450	253.1	53	5	100	0.7	90	4200	0.395	26.8	510
58	1090	5450	297	30	5	100	0.7	90	4200	0.390	22.1	515
59	1160	4640	142.8	28.65	4	100	0.43	160	2800	0.363	21.7	720
60	1160	4640	116.6	63.1	4	100	0.42	180	2800	1.029	22.6	785
61	1160	2320	325.1	96	6	0	0.35	160	2800	0.176	20.1	295
62	1180	7080	151.5	30	6	70	0.68	180	4200	0.777	32.1	985
63	1180	7080	91.2	54	6	70	0.72	180	4200	3.093	37.1	1255
64	1180	7080	76.6	30	6	70	0.72	180	4200	3.406	38.6	1320
65	1180	7080	132.5	41.5	6	0	0.55	180	4200	1.523	39	1130
66	1250	5100	207.4	85.1	5	0	0.38	180	4200	1.025	23.1	730
67	1250	5100	137.1	40.1	5	0	0.38	180	4200	1.388	24.6	785c
68	1250	5100	242.8	102.4	6	0	0.53	180	4200	0.587	35.5	635
69	1250	5100	188.5	75.1	6	0	0.54	180	4200	0.621	39.8	685
70	1290	3870	227.5	106	6	0	0.51	180	4200	0.670	37.2	395
71	1290	3870	140.6	40	6	0	0.58	180	4200	1.936	42	425
72	1410	6780	79.4	30	5	0	0.53	180	4200	2.69	46.3	1135
73	1490	3100	444.3	99	5	80	0.68	180	4200	0.476	14.3	285
74	1490	3100	364.4	42	5	80	0.71	180	4200	0.349	17.5	260
75	1490	3100	316.9	86	5	80	0.71	180	4200	0.598	19.8	315
76	1540	2350	240.9	86	6	100	0.7	0	2800	0.167	21.2	145
77	1540	2350	195.3	53.0	6	100	0.72	0	2800	0.128	24.3	145
78	1636	4980	224.3	109.3	4	0	0.51	180	4200	1.409	34.3	785
79	1660	8300	175.6	85	4	0	0.53	60	2800	0.445	35.48	1010
80	1790	5370	314.8	42	4	60	0.75	50	2800	0.713	17.9	630
81	1790	5370	205.2	30	4	60	0.75	50	2800	0.908	23.3	685
82	1800	9000	93.7	6	6	0	0.56	180	2800	4.094	39.6	1300
83	1800	9000	134.3	64	6	0	0.53	180	2800	2.913	37.5	1280
84	1850	8500	150.6	30	6	0	0.42	180	2800	0.987	34.5	920
85	2180	4360	159.7	73	5	0	0.48	60	4200	0.825	28.7	610
86	2180	4360	108.2	40	5	0	0.51	60	4200	1.132	33.3	685
87	3080	5600	274.6	50.9	5	0	0.36	180	2800	0.63	16.5	680
88	3080	5600	241.7	28.6	5	0	0.36	180	2800	0.621	18.6	685
89	3080	5600	127.5	63.1	6	0	0.45	110	2800	1.207	27.3	755
90	3080	5600	189.8	90.4	6	0	0.42	110	2800	0.784	25.3	710
91	3080	5600	94.9	46.9	6	0	0.46	110	2800	1.705	30.6	785
92	5590	6370	92.3	28.6	6	0	0.48	180	2800	5.093	23.1	1220
93	5590	6370	148.8	62.1	6	0	0.31	120	2800	3.228	21.3	1120