

Metallogenic Correlations for the Fe-Nb-REE Mineralization in the West Mine of the Bayan Obo Deposit, Inner Mongolia, China

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Abstract: The West Mine of the Bayan Obo deposit, located in the northern-central part of Inner Mongolia, China, is enriched in Nb, rare earth elements and iron (Nb-REE-Fe) mineral resources. This paper presents a combined method to explore metallogenic correlation of the Nb-REE-Fe mineralization at the Bayan Obo West Mine. The method integrates factor analysis and Back Propagation (BP) neural network technology into processing and modeling of geological data. In this study, the Nb and REE contents of samples were transformed into discrete values to analyze the correlations among the metallogenic elements. The results show weak mineralization correlations between Nb and REEs. Nb and U are closely related in the geochemical patterns, while Fe is closely related to both Th and Mn. LREEs are an important factor for the mineralization of the Bayan Obo deposit, while Fe and Nb can be considered as the results of passive mineralization. On the basis of a metallogenic correlation analysis, the factors affecting the Fe-REE-Nb mineralization were extracted, and the Nb mineralization model was established by the BP neural network. Based on the BP neural network data computing, the variability of the Nb concentration displays a coupled multi-factor nonlinear relationship, which can be used to reveal the inherent metallogenic elemental regularities and predict the degree of element mineralization enrichment in the mining area.

Key words: Factor analysis, BP neural network, metallogenic correlation, mineralization prediction modeling, Bayan Obo deposit

1 Introduction

The Bayan Obo deposit is an important mineral resources located within the metallogenic belt of Inner Mongolia, China, and it contains multiple mineral elements that are especially rich in iron (Fe), rare earth elements (REEs) and niobium (Nb) (Drew et al., 1990; Bayan Obo mining and metallurgical technology editing committee, 1994; Bai Ge et al., 1996; Smith et al., 2000; Zhang Zongqing and Yuan Zhongxin, 2003; Yang Xiaoyong et al., 2015; Fan et al., 2016). The Bayan Obo West Mine contains complicated geological features rich in Fe-REE-Nb that formed as a result of the multistage interactions of sedimentary sequences and hydrothermal-metallogenic processes, among others. These Nb and REE ore bodies were potentially concentrated under different

physicochemical conditions in a metallogenic environment. A wide range of primary and secondary geological events has affected the Bayan Obo area, resulting in variable behaviors of Nb and REEs belonging to a type of complex nonlinear process.

However, traditional metallogenic statistical methods are limited when addressing the mineralization among elements exhibiting a complex nonlinear relationship. To improve the accuracy of prediction analysis of target elements during metallogenic exploration in a region of enriched mineralization, previous studies have made contributions to the extraction of mineralized control variables and the metallogenic analysis of geochemical data analysis, especially in complex geological settings (Porwal et al., 2003; Lacassie et al., 2004; Shao Yongjun et al., 2007; Sun et al., 2009; Barnett and Williams, 2009; Dobretsov et al., 2010; Liu et al., 2015; Zhao et al., 2016;

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Chen Jianping et al, 2016; Guan Yao et al., 2017, Qiao Donghai et al., 2017). The analyses of large data sets and the study of the mineral prospecting and potential mineralization of geochemical data using statistical methods and neural networks have presented encouraging results. These methods (e.g., factor analysis, multiple linear regression, and decision trees), which have successfully solved numerous geological problems, have been applied to analyze variables aiming at extracting the geological factors associated with mineralization and to obtain a clearer comprehension of the data (Grunsky and Agterberg, 1988; Ord et al., 2009; Tolosanadelgado and Eynatten, 2010; Cheng Jianxun et al., 2005; Agterberg, 2012; Zhang Shiming et al., 2012; Liu et al., 2015; Zuo, 2017). Among these, factor analysis is often used to find and describe hidden representative variables, and it can extract these variables as factors and highly generalize the internal relations between variables without losing geological information (Reimann et al., 2002; Lin et al., 2014). Therefore, factor analysis could be used to evaluate and select the geological variables to obtain the metallogenic correlations for the complex metallogenic relationships within the Bayan Obo West Mine. Thus, the selected geological variables as reasonable parameters could be used to predict the mineralization of Nb in the BP neural network. Moreover, the research and application of neural networks in the field of geology have made great progress. There have been great improvements toward simplifying the calculation procedure, reducing the errors and improving the prediction accuracy of mineral enrichment. However, compared with the qualitative judgment of target minerals, the present challenge is primarily conducting an accurate quantitative calculation. Accordingly, neural network methods can provide a scientific quantitative calculation approach. Unfortunately, the design of neural networks and the definition of neural network structures are mainly based on experience and experiments on applications in different regions (Lacassie et al., 2004; Shao Yongjun et al., 2007; Zhao et al., 2016; Zaremotlagh and Hezarkhani, 2016). At present, few studies have conducted a metallogenic analysis in the Bayan Obo area.

In this paper, an applicative integrated methodology containing factor analysis and BP artificial neural network models was applied to perform a geochemical statistical analysis and a mineralization grade evaluation of Nb in the Bayan Obo West Mine. During an analysis of the geological controlling variables for the West Mine of Bayan Obo, the correlations among the multi-mineral mineralization of Nb-REE-Fe are evaluated through factor analysis. We focused on an investigation of the Nb orebody from the Bayan Obo west mine area. With appropriate input parameters and structure algorithms a set

of weighted interconnections among neurons can be adjusted according to the training of known samples that can simulate the multi-factor coupling process. The mineralization prediction model is used to characterize Nb-related element associations and calculate the concentrations of those elements. The element enrichment variations in the mineral resource exploration of the Bayan Obo West Mine area were obtained, providing evidence for the exploration and utilization of mineral resources and guidance for the prospecting of rare metals.

2 Geological Setting

The Bayan Obo deposit belongs to the transition zone between the North China Craton and the Central Asian Orogenic Belt in Inner Mongolia. The basement rocks are composed of the Lower-Proterozoic Wutai Group and the Mesoproterozoic Bayan Obo Group of metamorphic rocks in addition to a Carboniferous andesite and other units. The Cenozoic Erathem is mainly composed of red beds and sandy gravel deposits, which may have developed from deposition within inland basins or depressions (Wang Kaiyi et al., 2002; Lai Xiaodong et al., 2012; Xiao Rongge et al., 2012; Lai et al., 2013; Su, 2015; Yang et al., 2017). Among them, the Mesoproterozoic Bayan Obo Group is the main Fe-Nb-REE mineralization stratum; it has a large thickness with large changes in its lithofacies, which are mainly composed of quartzite, slate and carbonatite, and the distribution direction is roughly same as the extension direction of the fault (Yuan Zhongxin et al., 1995; Yang et al., 2000; Hao Ziguang et al., 2002).

In the Bayan Obo area, the folds and faults are well developed, and the geological structures are extremely complicated due to tectonic activities and the repeated intrusion of magma (Fig. 1). The West Mine is located on the west side of the wide ditch anticline and the Bayan Obo syncline, where the direction of the syncline axis is nearly east-west (EW). The West Mine is formed as a long and narrow area by compressional stresses with an EW synclinal fold axis. The wide ditch faults to the north of the ore deposit scarcely damaged the ore bodies, while inner secondary faults caused great damage to the ore bodies that was mostly caused by the infilling of acidic and basic magmas, which formed a certain number of acidic and basic dykes. Furthermore, a biotitized slate composes the syncline core, dolomite forms the limbs, and the transitional zone between them presents an interactive stratification (Institute of Geochemistry Chinese Academy of Sciences, 1988).

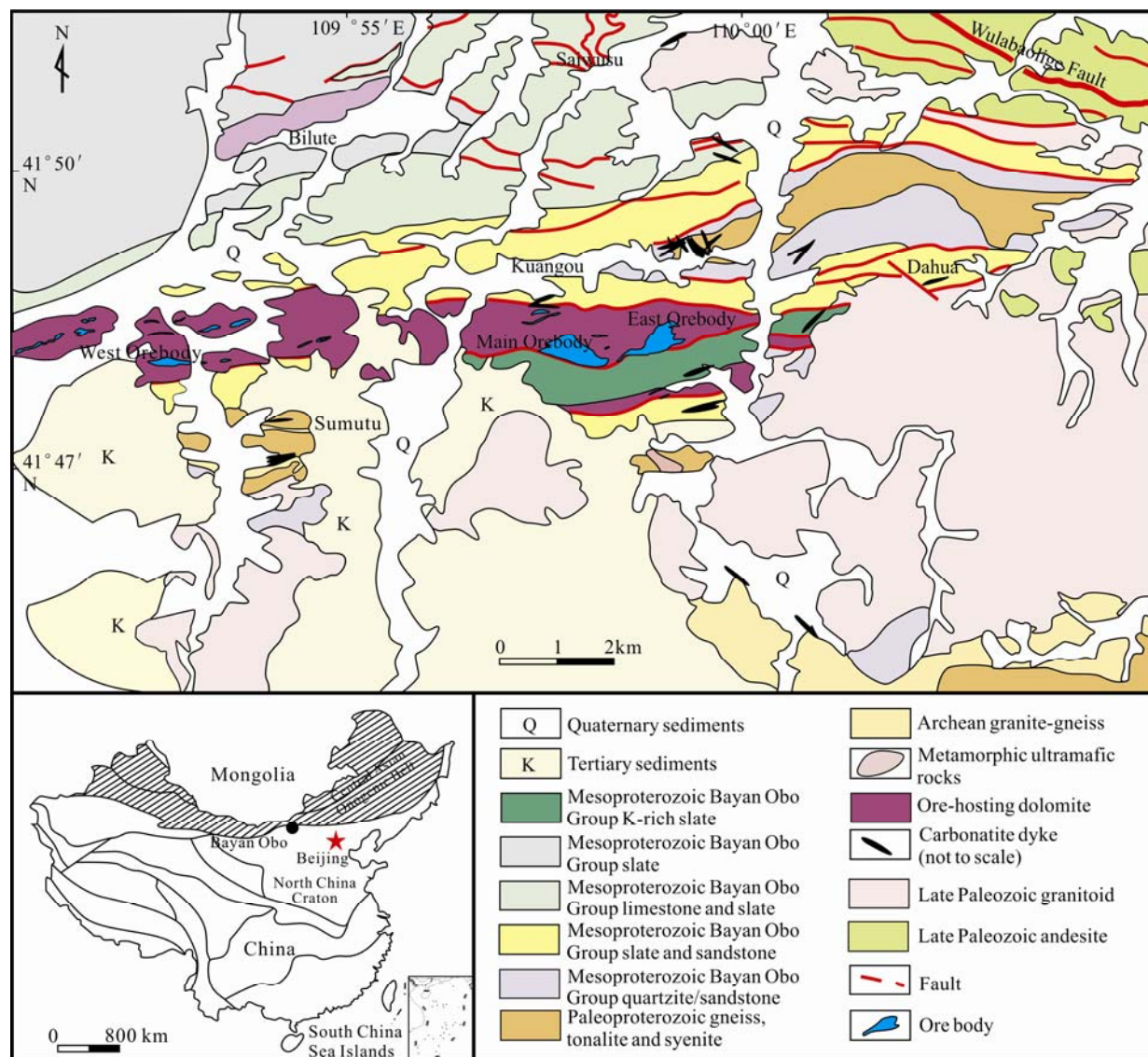


Fig. 1. Geological map with the location of the study area and the orebodies in the mineral field (after Fan et al, 2016).

3 Samples and Data Preparation

In this study, the exploration and sampling are both restricted to the H8 and H9 layers, which are the main distribution areas of Nb mineralization in the Bayan Obo West Mine. The samples were taken from ore bodies and weathering belts and the surrounding rocks, all of which were frequently affected by hydrothermal processes. To study the pattern of the geochemical concentrations of Nb and REEs, the sample rock types of the analysis included dolomite (DT), slate (ST), biotitized dolomite (BD), amphibolic dolomite (AC), aegirine dolomite (AT), fluorinated dolomite (FT), and slate (ST). The geological data including 31 samples, were analyzed at the CNNC Beijing Research Institute of Uranium Geology. Using an inductively coupled plasma spectrum analyzer (ELEMENT XR ICP-MS analyzer), the test method was

based on GB/T 14506.30-2010. The basic data consisting of the trace element concentrations are shown in Table 1.

It is generally accepted that the probability distributions of trace elements in rocks and minerals follow a lognormal or normal distribution (Carranza, 2011; Zaremotlagh and Hezarkhani, 2016; Zhao et al., 2016). The raw geochemical data are skewed and asymmetrical, as demonstrated in the histogram of REE contents in the Bayan Obo West Mine shown in Figure 2. The method of analyzing the skewness and kurtosis is a commonly used analysis method in statistical analysis. The statistical results of the geochemical trace element data from the Bayan Obo West Mine are shown in Table 2, in which the skewness and the kurtosis reflect the distribution characteristics of the data. In this paper, to avoid the potential effects of variations in the compositional data and the skewness of the geochemical data distribution on

Table 1 Chemical compositions analysis of rock samples in the Bayun Obo Fe-Nb-REE deposit

Samples	Rock classification	Si	Al	Fe	MgO	CaO	Na	K	MnO	Ti	P	Y	La	Ce	Pr	Nd	Sm
1	AC	11.69	4.03	17.41	9.95	22	0.111	2.45	2.2	0.214	1.72	34.7	1914	2776	295	861	73.7
2	DT	38.96	10.84	9.91	9.65	9.57	1.1	6.64	0.378	0.701	1.82	21.3	607	955	95	305	32.4
3	BR	36.22	9.61	16.95	15.26	4.29	0.1	8.76	0.172	1.56	0.209	44.8	1793	2908	348	1143	127
4	AC	33.8	2.48	8.94	12.18	18.36	2.28	2.64	0.766	0.087	1.19	55.9	431	877	103	392	56
5	AC	40.36	12.09	7.82	8.82	9.24	2.44	6.23	0.371	0.646	1.56	3.47	64.7	143	16.4	55.1	5.61
6	AC	13.29	0.16	8.38	14.4	25.9	1.16	0.18	0.8	0.031	0.744	33.4	1679	2650	291	844	81.1
7	DT	2.27	0.611	7.14	15.9	28.19	0.056	0.297	0.812	0.063	2.07	20.5	894	1554	149	477	45.2
8	AC	37.41	10.13	15.27	11.28	5.77	2.3	5.66	0.453	0.448	1.26	97.9	3401	7280	1020	3430	290
9	BR	26.73	9.6	14.66	12.45	12.39	0.278	6.07	0.664	1.09	0.551	21.7	1601	2120	222	639	53
10	AC	29.76	2.18	11.69	10.6	20.25	2.16	2.13	0.739	0.121	3.43	13.3	360	674	78.4	279	34.2
11	DT	29.01	6.63	12.09	12.53	14.4	0.83	5.38	0.639	0.318	1.54	29.5	1193	1774	162	487	42.9
12	BR	28.72	7.87	12.45	12.23	13.65	0.814	5.8	0.415	0.348	4.65	45	1560	2007	209	605	57.6
13	DT	27.63	7.46	13.78	12.12	12.57	0.991	5	0.661	0.497	1.95	46.1	262	532	66.3	256	50.2
14	AC	22.25	0.175	7.33	14.38	24.34	1.72	0.322	0.813	0.038	0.824	111	2625	4193	460	1366	153
15	ST	55.06	16.18	6.17	3.92	2.32	7.85	1.79	0.277	0.17	0.594	30.4	995	1624	155	507	63.9
16	AC	32.3	2.36	10.86	11.05	19.66	2.44	2.2	0.809	0.139	2.4	31.9	2763	4217	452	1314	110
17	ST	56.35	14.36	7.48	4.21	0.598	1.19	11.19	0.075	0.379	0.139	18.3	471	834	85.6	269	34.2
18	BR	45.63	13.91	9.61	6.82	6.63	4.91	4.1	0.193	0.621	0.6	77.6	2382	3688	409	1253	136
19	BR	36.76	27.14	12.64	4.6	3.12	3.11	4.56	0.658	0.533	0.165	15.1	4257	5811	549	1373	80.7
20	DT	7.73	0.273	8.39	14.62	28	0.721	0.254	0.852	0.031	0.941	113	3448	5543	649	2154	242
21	AT	34.38	7.52	6.81	2.53	21.04	4.12	0.672	0.617	0.081	1.14	17.9	506	1041	126	451	44.6
22	DT	5.94	0.292	8.07	14.16	29.34	0.434	0.282	0.774	0.032	3.93	35.2	2334	3609	384	1147	101
23	DT	3.85	0.267	8.59	14.9	28.17	0.331	0.179	0.785	0.065	2.25	79	12890	17955	1708	4349	284
24	FT	9.94	2.99	20.76	7.31	26.3	0.12	2.22	1.18	0.537	1.88	19.2	2958	4044	396	1020	65.8
25	ST	50.17	16.41	11.93	4.79	1.14	5.76	3.76	0.51	0.855	0.301	63.7	710	1182	117	383	49.7
26	BR	44.36	17.57	7.15	6.15	5.68	4.51	3.93	0.121	0.977	0.704	14.3	627	1105	121	428	43.7
27	AT	53.53	7.59	19.41	5.18	0.674	0.16	3.56	0.142	0.651	0.46	14.2	237	450	51.5	181	20.6
28	FT	7.12	0.235	8.67	11.55	28.76	0.659	0.257	0.792	0.037	0.962	13.8	1771	2325	232	618	40.1
29	BR	22.37	5.25	14.31	10.65	18.55	0.191	3.34	0.746	0.406	0.322	62.7	5116	7559	759	1998	155
30	DT	6.46	2.53	9.66	8.44	37.26	0.097	1.51	0.616	0.216	0.474	40.3	260	525	63.7	237	33.9
31	BR	45.35	9.65	9.73	7.92	9.21	2.85	3.18	0.366	0.674	1.63	44.1	1993	2981	317	956	108

Samples	Rock classification	Eu	Gd	Tb	Dy	Ho	Er	Tm	Yb	Lu	Th	U	Ta	Nb	LREE	HREE	REE+Y
1	AC	15.4	43.4	3.74	10.7	1.45	3.37	0.307	1.4	0.143	61.4	7.09	2.72	282	5935.1	64.51	6034.31
2	DT	9.05	19.9	2.05	7.13	0.966	1.96	0.207	0.831	0.095	26.4	17.1	16	1100	2003.45	33.139	2057.889
3	BR	32.3	72.1	6.89	17.8	2.29	4.55	0.355	1.66	0.177	86.4	11.8	0.287	1121	6351.3	105.822	6501.922
4	AC	16.4	36.9	4.68	17.5	2.61	5.32	0.67	3.44	0.439	5.43	1.59	0.892	3990	1875.4	71.559	2002.859
5	AC	0.661	2.93	0.319	0.931	0.124	0.258	0.033	0.162	0.016	5.72	0.859	0.675	1399	285.471	4.773	293.714
6	AC	14.9	53	4.45	11.7	1.48	3.39	0.289	1.56	0.192	65.4	3.37	2.76	746	5560	76.061	5669.461
7	DT	9.63	39.8	3	8.52	0.958	3.01	0.202	1.26	0.164	62.4	7.27	5.92	17	3128.83	56.914	3206.244
8	AC	57	130	10.4	24.1	3.21	8.98	0.675	3.91	0.38	418	1.43	0.91	3443	15478	181.655	15757.56
9	BR	5.83	30.1	2.34	6.46	0.896	2.15	0.202	0.957	0.111	19.4	1.89	3.17	1172	4640.83	43.216	4705.746
10	AC	7.12	16.6	1.34	4.19	0.548	1.22	0.11	0.683	0.068	36.5	2.3	0.298	1458	1432.72	24.759	1470.779
11	DT	8.53	29.6	2.96	10.1	1.4	2.84	0.23	1.07	0.103	31.2	11.6	2.86	1471	3667.43	48.303	3745.233
12	BR	15.8	43.8	4.38	15.1	2.13	4.15	0.364	1.75	0.156	23.6	0.942	0.066	2663	4454.4	71.83	4571.23
13	DT	15.8	30	4.22	15.5	2.05	3.51	0.323	1.48	0.18	9.54	11.6	4.32	1469	1182.3	57.263	1285.663
14	AC	42.4	98.6	8.37	24.7	3.84	8.03	0.72	3.95	0.418	189	5.7	2.49	457	8839.4	148.628	9099.028
15	ST	14.3	52.5	4.43	12.5	1.34	3.53	0.218	1.24	0.148	31.5	1.98	2.14	148	3359.2	75.906	3465.506
16	AC	24.2	66.4	5.17	12.2	1.57	3.6	0.236	1.09	0.119	71.3	5.25	2.2	1188	8880.2	90.385	9002.485
17	ST	7.36	18.1	1.66	5.76	0.743	1.51	0.102	0.583	0.063	68.8	0.72	1.06	220	1701.16	28.521	1747.981
18	BR	37.2	93.7	8.94	27.7	3.89	8.24	0.789	3.61	0.321	25.1	0.757	0.056	836	7905.2	147.19	8129.99
19	BR	17.2	68	3.98	6.56	0.802	2.67	0.111	0.637	0.065	23.5	3.88	0.194	549	12087.9	82.825	12185.83
20	DT	65.4	149	14.9	46	6.03	11.1	0.854	3.21	0.287	39.9	0.699	0.24	491	12101.4	231.381	12445.78
21	AT	10.3	22.4	1.91	5.24	0.725	1.7	0.17	1.11	0.137	66.7	1.93	2.34	402	2178.9	33.392	2230.192
22	DT	25.6	68.4	5.45	12.8	1.6	3.67	0.252	1.2	0.133	75.4	6.54	2.35	107	7600.6	93.505	7729.305
23	DT	64.3	224	16.2	33	3.55	9.52	0.447	2	0.189	108	2.5	0.285	791	37250.3	288.906	37618.21
24	FT	14.3	51.6	3.32	7.35	0.935	2.73	0.162	0.87	0.068	17.4	2.37	0.526	1327	8498.1	67.035	8584.335
25	ST	11.7	31.3	3.3	10.9	1.59	3.52	0.356	1.9	0.237	69.5	6.28	3.12	219	2453.4	53.103	2570.203
26	BR	3.77	17.3	1.38	3.06	0.483	1.32	0.141	0.715	0.093	45.1	1.16	0.634	718	2328.47	24.492	2367.262
27	AT	3.91	12.8	1.44	4.72	0.638	1.2	0.098	0.477	0.055	4.83	4.65	2.97	212	944.01	21.428	979.638
28	FT	8.39	29.5	2.21	4.7	0.648	1.62	0.117	0.484	0.045	15.6	2.11	0.066	270	4994.49	39.324	5047.614
29	BR	39.1	122	9.37	21.7	2.7	6.14	0.466	2.24	0.223	155	9.77	0.078	173	15626.1	164.839	15853.64
30	DT	10.3	23.1	3.24	12.5	1.75	3.5	0.419	2.76	0.395	21.6	33.8	0.428	1007	1129.9	47.664	1217.864
31	BR	28.8	62	5.58	14.6	1.81	4.08	0.327	1.68	0.194	74.6	2.83	1.42	404	6383.8	90.271	6518.171

Note: DT: dolomite; ST: slate; AC: amphibolite dolomite; FT: fluorinated-dolomite; AT: Aegirine dolomite; BR: biotitization-dolomite. Principal element (%), Microelement (ppm).

the multivariate statistical analysis, a log transformation is applied to the data prior to their use in the multivariate analysis (Reimann and Filzmoser, 2000; Liu et al., 2015).

The transformation alleviates the influences of the skewness of the raw data and the distributions of the element concentrations, and thus, all of the data conform

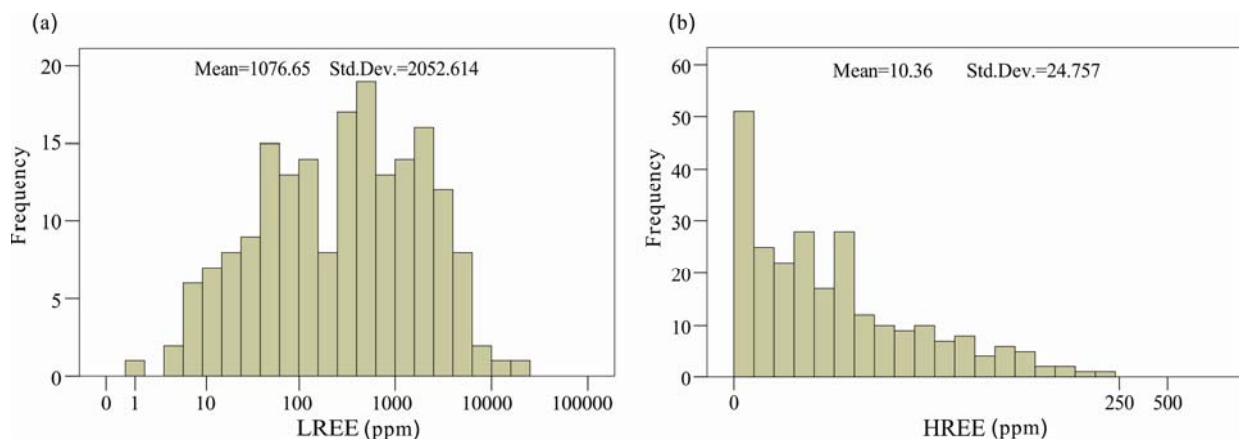


Fig. 2. Histograms of REE content of samples in Bayan Obo West Mine. LREE and HREE represent light and heavy rare earth elements, respectively.

Table 2 The statistics of geochemical data of rare metals and REE contents in west orebody (ppm)

Compositions	Mean	Maximum	Minimum	Std.Deviation	Median	Skewness	Kurtosis
Y	40.944	113.000	3.470	29.190	33.400	1.178	0.705
La	2003.313	12890.000	64.700	2388.574	1601.000	3.373	14.510
Ce	3062.452	17955.000	143.000	3396.726	2120.000	3.051	12.085
Pr	325.481	1708.000	16.400	344.528	222.000	2.551	8.178
Nd	960.552	4349.000	55.100	944.306	618.000	2.244	5.639
Sm	87.584	290.000	5.610	72.368	57.600	1.710	2.479
Eu	20.547	65.400	0.661	17.479	14.900	1.407	1.237
Gd	56.737	224.00	2.930	47.484	43.400	1.865	4.156
Tb	4.891	16.200	0.319	3.782	3.980	1.614	2.536
Dy	13.410	46.000	0.931	9.757	11.700	1.572	3.065
Ho	1.766	6.030	0.124	1.279	1.480	1.525	2.846
Er	3.948	11.100	0.258	2.681	3.500	1.217	0.879
Tm	0.321	0.854	0.033	0.218	0.252	1.090	0.387
Yb	1.610	3.950	0.162	1.062	1.260	1.006	0.059
Lu	0.175	0.439	0.016	0.115	0.148	0.993	0.193
Th	63.039	418.000	4.830	78.235	39.900	3.437	14.363
U	5.541	33.800	0.699	6.659	2.830	2.875	10.439
Nb	962.903	3990.000	17.000	937.810	746.000	1.873	3.745
Ta	2.048	16.000	0.056	2.970	1.060	3.691	16.718
Zr	29.351	152.000	2.880	29.431	21.900	2.625	9.412
Hf	2.511	10.300	0.331	1.979	1.920	2.196	7.085
ΣLREE	6459.928	37250.300	285.470	7071.310	4640.830	2.988	11.687
ΣHREE	82.858	288.910	4.770	64.234	67.035	1.653	2.827
ΣREE	6542.786	37539.210	290.240	7127.881	4684.046	2.977	11.614
ΣREE+Y	6583.730	37618.210	293.710	7143.291	4705.746	2.970	11.562

Original data are listed in Table 1.

to the statistical characteristics of a normal distribution. Therefore, the data comprising the element contents are tested using the quantile-quantile (Q-Q) plot method in this paper. For a more intuitive analysis, the rare metals (Nb and Th) and rare earth elements (La, Ce, Tb, and Gd) with higher concentrations in the mining area are shown in the Q-Q plot (Fig. 3) to perform a distribution test on the data. The LREEs (La and Ce) have good fits, while the fits for Nb, Th, Tb, and Gd, which display less smoothed values, may indicate a little heterogeneity of the distributions of these elements.

4 Results and Discussion

4.1 Correlation analysis of metallogenic elements

The metallogenic relations in the Bayan Obo deposit are

complicated. To analyze the metallogenic correlations among the elements related to the Nb concentration, the geological data were employed to describe the correlations among the mineralized elements through factor analysis, which could be used to describe the variabilities among the observed and correlated variables in terms of a potentially lower number of unobserved variables called factors. The basic data construction is represented by a few new, imperative variables that can most effectively reflect the main information represented by the original variables and explain the interdependencies among them. This means that an interpretation of the principal component factors corresponds to the tracer of geological processes and the re-division of geochemical fields (Reimann et al., 2002; Pu Xiugang et al., 2013; Huang Xiaowen et al., 2014; Afzal et al., 2016).

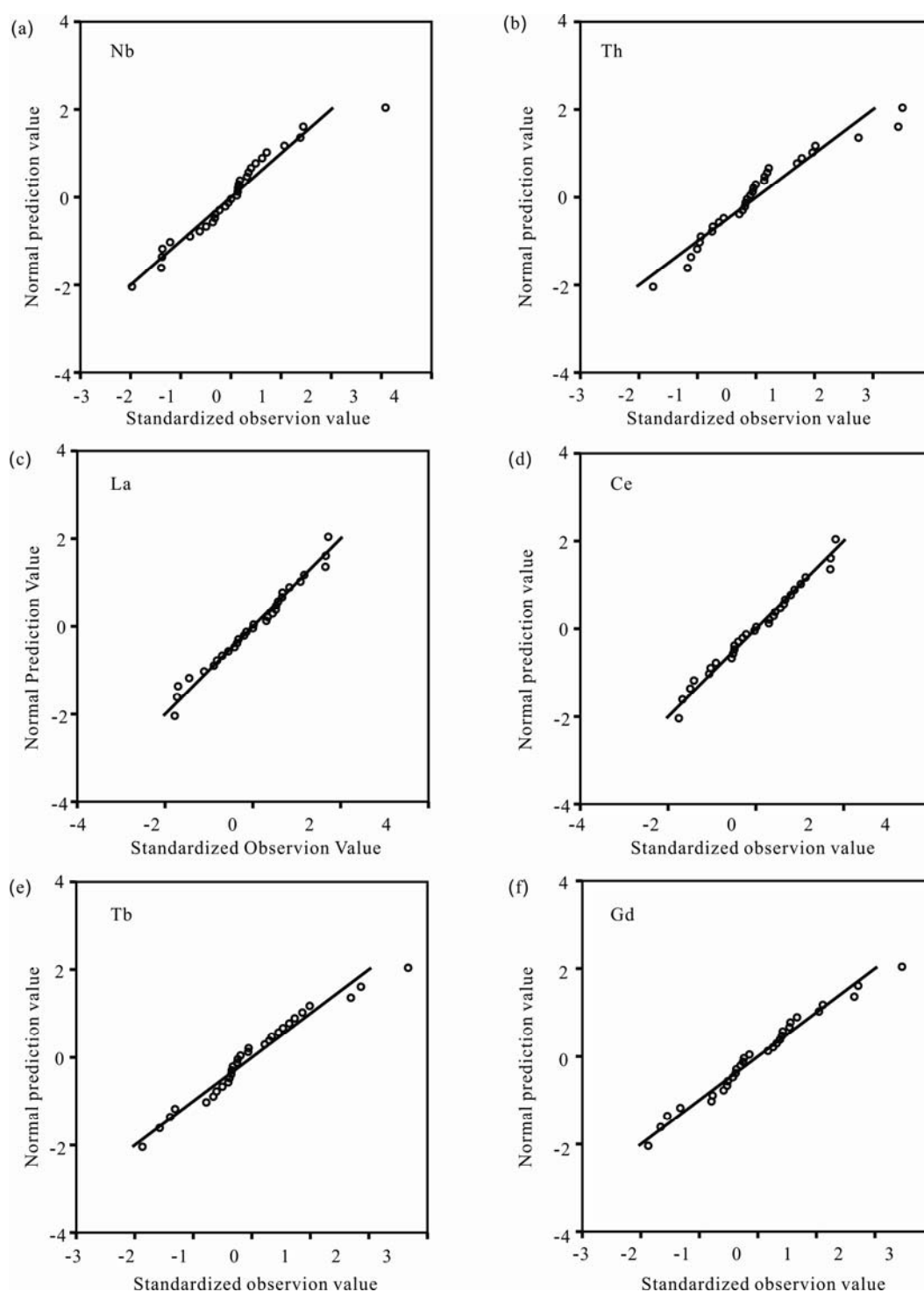


Fig. 3. Q-Q plots of log-transformed data of (a) Nb; (b) Th; (c) La; (d) Ce; (e) Tb; (f) Gd.

The present factor analysis is based on a correlation search of the main factors as well as a potentially symbiotic combination of the elements. The new basic factors obtained from the original variables are independent of one another, and the relationships between the geological variables and characteristics are analyzed. The associations among the Nb-related mineralization elements are evaluated via certain overprinting

information that can be extracted and integrated into the representative factors. Therefore, the subset of each factor can be used to identify elements and predict the enrichment extent of Nb and certain REEs, thereby reflecting the intrinsic relationship with the original source. The geological variations of twenty-eight elements are carried out, and the log transformation is applied to the raw data processing. The Bartlett test is required for the

data correlation test. Moreover, the results of the Kaiser-Meyer-Olkin (KMO) test factor analysis can be accepted (KMO value = 0.686; if the KMO value is between 0.6 and 1, the factor is appropriate for the analysis) (Liu Jiangtao and Liu Lijia, 2017). To explore the element associations, six representative factors are extracted for the data set with a varimax rotation of the results. The load factor reflects the correlation by the combination of the different elements. By using the accumulative contribution > 90% as a constraint (shown in Table 3), the factor analysis selects six main factors that account for 90.79% of the total variance of the data source. The accumulative contribution rate does not change from before to after the rotation, indicating that the total amount of information is not lost. After rotation, factors 1 and 2, factors 3 and 4, and factors 5 and 6 account for approximately 26%, 12%, and 7.5% of the total amount of data, respectively. This probably indicates that factors 1 and 2 explain the largest part of the overall contribution to the mineralization. The influences of the factors decrease successively for factors 3, 4, 5, and 6.

The elements of factor 1 include Ce, La, Pr, and Nd, while those of factor 2 include Tm, Yb, Lu, and those of factor 3 include Eu, Tb, Sm, Gd, Dy, Ho, Er, and Y; these combinations are interpreted to suggest that the enrichment of REEs plays the most important role associated with Nb mineralization. The elements of factor 4 include K, Ti, Si, Al, and Na, while those of factor 5 include Mg, Ca, P, Fe, Mn and Th; these groups may reveal that the correlation among the major elements is highly positive, implying a high Th concentration in the

iron ore. Factor 6 is dominated by U and Nb, which likely represent Nb mineralization. In terms of the quantifiable impact factors, the enrichment of REEs is four times as much as those of Nb and U and three times that of Fe. Although the Bayan Obo deposit is enriched in Fe and Nb, their existence can be considered as the result of “passive mineralization” since factors 5 and 6 have the lowest contribution to mineralization. The two-dimensional principal component diagram is shown in Figure 4.

Clustering analysis based on the above factor analysis provides a classification of the elements and a quantification element index of the degree of similarity; according to these indicators and the similarity degree, the elements or samples can be divided into different classes (Templ et al, 2008). The distance metric matrix of the cluster analysis in a Euclidean space is shown in Table 4 to represent the symbiotic relationship between the elements and classification evaluation. Because the light rare earth elements (LREE) and heavy rare earth elements (HREE) have a high internal correlation, the cluster

Table 3 Partitioning of total variance

Factor	After rotation		
	Eigenvalue	Contribution rate (%)	Accumulative contribution (%)
1	7.31	26.12	26.12
2	7.29	26.03	52.15
3	3.38	12.07	64.22
4	3.21	11.48	75.70
5	2.16	7.73	83.43
6	2.06	7.36	90.79

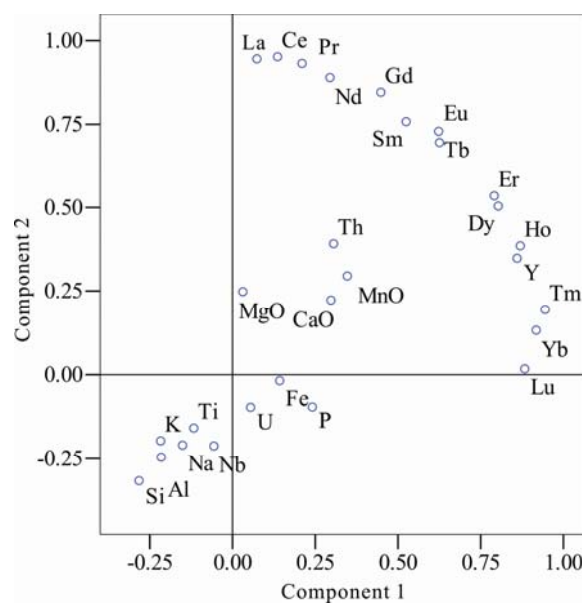


Fig. 4. Two dimensional principal component analysis.

Table 4 Euclidean space distance metric matrix

Observed value	Euclidean space distance metric													
	Si	Al	Fe	MgO	CaO	Na	K	MnO	Ti	P	LREE	HREE	Th	Nb
Si	0.000	3.894	7.714	10.006	10.734	4.665	4.824	9.999	5.487	8.963	9.651	9.623	8.775	7.422
Al	3.894	0.000	7.617	10.041	10.496	4.921	4.990	9.473	5.042	9.178	9.311	9.333	8.227	7.966
Fe	7.714	7.617	0.000	7.816	8.453	9.165	6.551	6.666	5.787	7.859	7.491	7.192	5.329	6.690
MgO	10.006	10.041	7.816	0.000	5.279	9.848	8.594	6.460	8.490	6.139	6.435	6.636	7.851	7.067
CaO	10.734	10.496	8.453	5.279	0.000	9.495	10.176	4.866	9.957	6.263	5.589	5.358	7.014	8.240
Na	4.665	4.921	9.165	9.848	9.495	0.000	7.843	9.060	7.433	8.619	9.045	8.983	8.707	7.993
K	4.824	4.990	6.551	8.594	10.176	7.843	0.000	9.430	4.400	8.473	9.133	9.113	8.056	6.604
MnO	9.999	9.473	6.666	6.460	4.866	9.060	9.430	0.000	9.311	6.760	5.139	5.137	3.722	8.153
Ti	5.487	5.042	5.787	8.490	9.957	7.433	4.400	9.311	0.000	9.020	8.796	8.760	7.780	7.485
P	8.963	9.178	7.859	6.139	6.263	8.619	8.473	6.760	9.020	0.000	7.482	6.803	7.714	7.156
LREE	9.651	9.311	7.491	6.435	5.589	9.045	9.133	5.139	8.796	7.482	0.000	4.229	5.193	8.381
HREE	9.623	9.333	7.192	6.636	5.358	8.983	9.113	5.137	8.760	6.803	4.229	0.000	5.637	7.811
Th	8.775	8.227	5.329	7.851	7.014	8.707	8.056	3.722	7.780	7.714	5.193	5.637	0.000	8.082
U	7.422	7.787	6.690	7.067	8.240	7.993	6.604	8.153	7.485	7.156	8.381	7.811	8.082	0.000
Nb	7.422	7.966	7.091	6.906	7.951	7.902	6.809	7.965	7.617	6.703	8.721	8.164	8.394	3.241

analysis of these two groups of elements is conducted using two combinations based on past experience of geochemical analysis.

The essential relationships between the elements (combinations) and the tree diagram are shown in Figure 5. The tree diagram shows the correlation between each element (combination) and the potential relationships of the Bayan Obo mineralization. Th is closely related to Fe and Mn, and thus, the difficult separation of Th and Fe encountered during the beneficiation process may be due to the genesis of the Bayan Obo deposit. There are certain mineralization differences among Fe, REEs and Nb. The mineralization correlation between Nb and the REEs is weak, indicating a separation during the mineralization of a Nb ore body and a rare earth ore body between different layers of western ore, which is the same conclusion reached by a field geological survey. An analysis of geological data in the mining area in addition to exploration and sampling investigations indicate that Nb is often enriched in the form of a pyrochlore belt (comprising aegirite and diopsidite Nb ore and part of biotitized ore), in which the REE content is relatively

leaner. Meanwhile, the parts of ore-bearing dolomite that are more concentrated in REEs always contain less Nb (Gao Jiuyan et al., 1999; Liu Tiegeng et al., 2012; Yuan Zhongxin et al., 2012). This tendency of the separation between Nb and REEs in the deposition process shows that Nb and REEs have different mineral deposition characteristics during hydrothermal transport in similar environments. A study of metallogenic correlations demonstrates that Nb has the closest Euclidean distance to U, indicating that Nb has the best correlation with U; thus, it can be speculated that Nb and U experience the same mineralization process. It is possible that U and Nb both belong to lithophile elements in high-temperature hydrothermal minerals, suggest that they mineralize in a hydrothermal environment. Previous studies on metallogenic effects also suggesting the influence of hydrothermal activity from a mantle source on mineralization (Ni Pei et al., 2003; Qin Chaojian et al., 2007; Wang Kaiyi et al., 2010; Lai et al., 2015; Huang et al., 2015).

During an analysis of the distribution of rare earth elements and trace elements in the West Mine of the Bayan Obo deposit, Nb and LREEs have obvious enrichment characteristics (as shown by the rare earth element standardization diagram and trace element spider web diagram in Figure 6) compared with various types of rock samples. Generally, the Bayan Obo west mine is enriched in LREEs; most of the samples have no obvious negative Eu anomaly. It displays not only high Nb and Th contents but also lower contents of U and Ta. With the obvious enrichment in Ba, Nb, and LREEs as well as with the depletion of U, P, K, Ta, and Ti, the enrichment and depletion of most elements present different elements yet similar trends among the different types. These findings indicate that these elements may have similar material sources or metallogenic processes (Liu Tiegeng, 1986; Yang XueMing and Yang XiaoYong, 1998; Zhang Yuxu et al., 2008; Sun Jian et al., 2012).

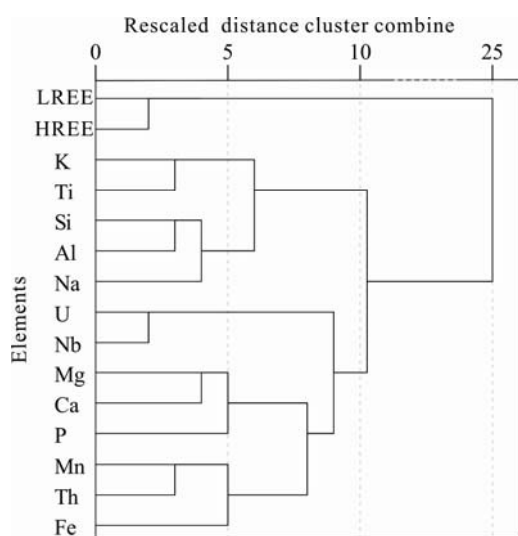


Fig. 5. Tree diagram of clustering process.

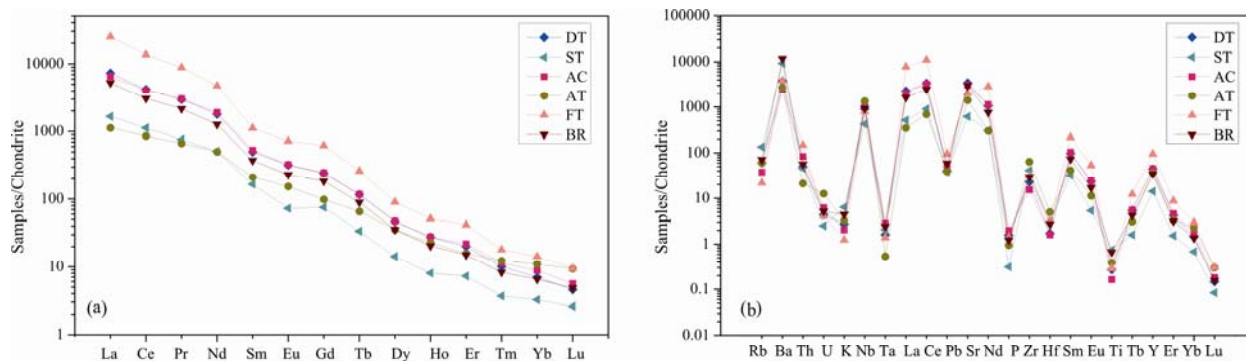


Fig. 6. Rare-earth element standardization diagram (a); trace element spider diagram (b).

4.2 Prediction calculation of Nb mineralization

The above analysis of the correlations between the different elements indicates that different correlations exist between each element with regard to their mineralization. Because the variations in the elements can reflect the mineralization processes of the ore body, it is possible to select the main geological information that affects the mineralization of target elements based upon all of the elements by means of factor analysis. These selected elements are then used as the input variables to construct a BP neural network model to reduce the dimensionality for an effective prediction.

Especially for the various mineralization conditions in the Bayan Obo deposit, the BP neural network is characteristically capable of parallel distributed processing, self-organization, self-adaptation, self-training, robustness and fault tolerance, all of which can be used to solve nonlinear geological analysis problems (Shao Yongjun et al., 2007; Lu Lu et al., 2012; Ziaii et al., 2012; Zuo et al., 2017).

The metallogenic prediction neural network model includes both training and test processes (Haykin, 2011; Ziaii et al. 2011; Son et al. 2016). The process is shown as a flow diagram in Figure 7. The training process uses samples in the standard model to train the neural network. The nonlinear mapping relationship between the input and output factors is established by adjusting the weights of the neurons according to the input parameters. After the network has been trained, in the test process, the concentrations of the elements are used as input data to obtain the calculated results associated with the mineralization of Nb. The most important principle for designing a BP neural network model is to make the output value approach the actual value to the greatest extent possible. According to the data characteristics of the Bayan Obo area, the algorithm, structure design, and error discrimination of this network are all improved. With regard to the accuracy of the output, an error analysis is used to confine the structure error to a small scale while simultaneously adjusting the error to minimize the separation between the computed prediction output and the actual value. Thus, it is reasonable to predict the

mineralization of Nb in the West Mine of Bayan Obo by using the BP neural network based on the metallogenic correlations.

Based on the actual situation, the number of network layers, the number of hidden layer neurons, and the activation function are all considered when the BP neural network model structure is established. The BP neural network used herein has a three-layer structure: an input layer with n neurons, a hidden layer with m neurons, and an output layer with one neuron. X through X_n are the input elements, which represent the geochemical components of the geological variables associated with the Nb mineralization. The output value Y corresponds to the predicted value of Nb. The BP neural network structure diagram is shown in Figure 8.

The metallogenic prediction model is actually a fitting evaluation for the enrichment grade of the Nb metallogenic concentration. In industrial applications, qualitative outputs are commonly used. This output variable in a two-state assignment is applied to identify the mineralized grade of the sample and determine whether it reaches an industrial grade. To describe the variation in the Nb mineralization accurately, the numerical value of the prediction would be more appropriate as the output. In this study, the Nb mineralization prediction model consisting of a network with a three-layer structure is constructed based on the element concentrations. The calculation results obtained by the model represent the predicted mineralization value associated with Nb. The modeling, which is based on the MATLAB software, consists of the following steps:

(1) Determining the input geological variables. The variables consisting of the element compositions of the rocks can effectively record the depositional conditions during the mineralization process. The geochemical components associated with the Nb mineralization of twenty-eight elements are used as input variables. The output represents the predicted value of the Nb content in ore-bearing rocks.

(2) Setting the training data. A training data set is constructed for the BP neural network model. All of the variables of the input values are transformed to values of

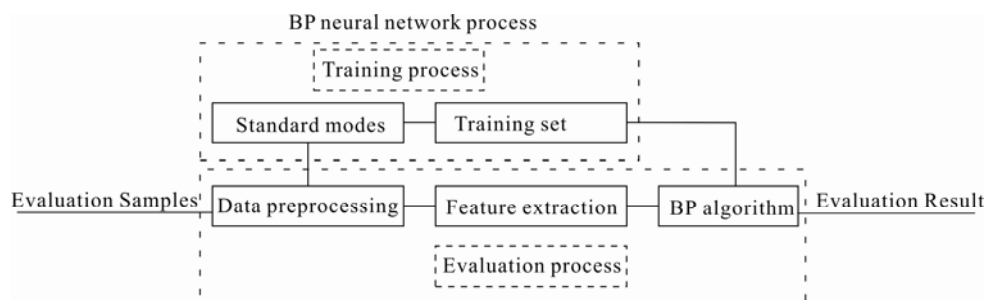


Fig. 7. BP neural network model evaluation process schematic.

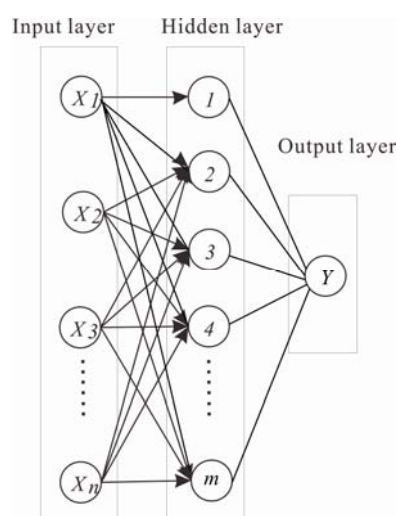


Fig. 8. Neural network structure.

[0, 1] in the calculation process.

(3) Selecting the optimal modeling parameters. The numbers of hidden layers and neurons are selected by repeated trial and error by traversing the hidden layer nodes to optimize the process. According to the debugging results for the number of neurons and activation functions, the scheme with the smallest error is chosen. The training error curve is shown in Figure 9, which demonstrates the evolutionary process of the squared error curve of the training monitoring data. The curve basically starts from an initial square error of 10^{-2} and then converges to 10^{-5} after 15,000 epochs. The results show that the output error is within a reasonable range compared with the actual value (except for the high anomaly values), and the accuracy shows that the algorithm is applicable.

(4) Predicting and explaining the results. The output value of a group of ten samples is randomly selected from among the test results, and the correlation coefficient of the corresponding actual value is $R = 0.8198$. According to the results of the factor analysis, the input variables are replaced with seven elements (U, Ti, Fe, Mg, K, Si, and P) that have closest correlations with Nb in Table 4. The test results of two different sets of input variables are then obtained successively. By selecting the same group of output values from the seven elements used as input values, the correlation coefficient between the output value and the actual value is $R = 0.8069$. After reducing the dimensionality of the input variables using the extraction results of the factor analysis, the correlation coefficients of the results computed by two different input variables are basically consistent. This indicates that the factors of the dimensionality reduction can basically recover the influences of the Nb enrichment information. Ten prediction results are randomly selected from each set of output values, and the predicted values of the two

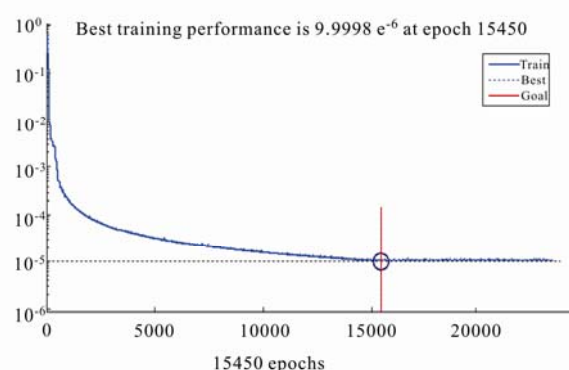


Fig. 9. Training monitoring data squared error curve evolution.

groups are compared with the corresponding actual values, as shown in Figure 10. The results show that the predicted value at 2000 ppm is relatively accurate and reliable. The high initial value above 2500 ppm is a high-value anomaly, and the predicted value is relatively offset. A high value indicates a high grade of mineralization within the metallogenic enrichment area, although the BP neural network model for the calculation of abnormally high values contains offset errors, and thus, it has a smaller practical influence on the actual identification of mineralization.

According to the Nb content, the samples can be divided into three groups: those below 500 ppm, 500–2000 ppm, and those above 2000 ppm. The samples with actual values below 500 ppm mostly originate from slate and partly from dolomite. The variation in the Nb content among the different samples of aegirine dolomite is

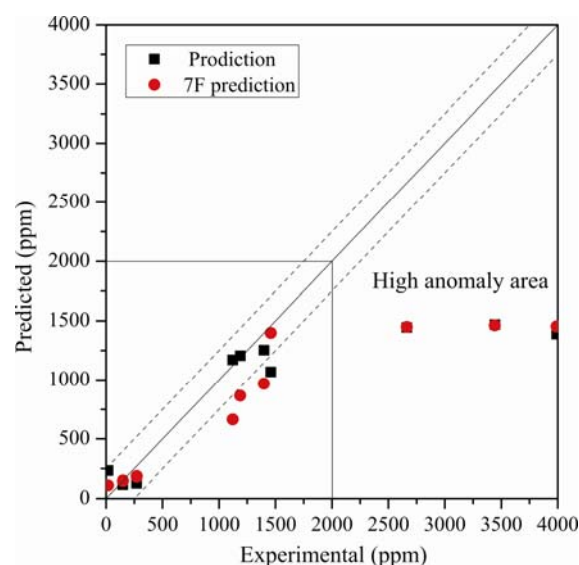


Fig.10. Comparison of prediction values with actual values.

7F represent imply seven elements resulted from factor analysis which are considered as the prediction modeling inputs, because they have closest correlation to the element Nb.

substantial. Compared with the other rock types, the dolomite samples with either amphibolization or biotitization have certain guiding effects on the enrichment of Nb. In conclusion, according to the actual demand of the mining area, the mineralization grade of Nb in different rock types can be predicted and sorted through the calculation of chemical analysis data. The metallogenic prediction model aimed at target exploration elements within the mine can provide metallogenic indications for the Bayan Obo West Mine, thereby providing new ideas and methods for detecting the mineralization of Nb and rare earth elements in the Bayan Obo area through data exploration.

5 Conclusions

The present method integrates factor analysis and BP neural network technologies into processing and modeling of geochemical data, and it is applied to analyze the correlations among metallogenic elements and predict the Nb mineralization. The results of this study draw the following conclusions:

(1) Based on geological data, the metallogenic correlations among the Fe-Nb-REE geochemical patterns in a complex geological setting can be obtained by an analysis of the relationships among mineralization elements. There is a certain differentiation between the enrichment of REEs, Fe and Nb. The mineralization correlation between Nb and REE is weak. Nb and U are closely related; meanwhile, Fe is closely related to both Th and Mn. LREEs are the most important factors on the mineralization throughout the Bayan Obo West Mine, while Fe and Nb can be considered the results of passive mineralization. This is consistent with the observations of field exploration surveys and the geological characteristics of the Bayan Obo West Mine.

(2) The parameters selected as the model inputs during factor analysis were applied to predict the Nb enrichment. Based on the BP network, the mineralization prediction model provides reliable results regarding the Nb enrichment in different rock types. The integrated method consisting of factor analysis and BP neural network technologies in this study can extract the mineralization controlling factors, which are beneficial for predicting the extent and location of mineralization, and further predict the mineralization enrichment of different elements that may exist throughout the Bayan Obo area.

(3) The influences of a variety of factors that led to the enriched behavior of Nb mineralization display a type of nonlinear relationship. This relationship can be used to exploit the variations in the concentrations of Nb through

data mining to obtain the metallogenic pattern of enrichment of Nb.

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