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Prediction of Failure Risk for Underground Casing Pipe Based on Geostatistics

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Abstract. Failure analysis of underground casing pipe is very important for engineering protection. Failure of underground casing pipe is affected by many factors, and shows very strong spatial variability. Therefore, a predictive model is constructed based on geostatistics, in which spatial variability is taken into account. Through the spatial variability analysis of influence factors, interpolating images can be worked out with kriging and mathematical fitting techniques. As an application example, the failure risk is calculated by this model with interpolating images. The distribution of failure risk of underground casing pipe is investigated, and some advice is proposed.

Introduction

In recent years, there are many researches on the mechanism of underground casing pipe failure, and the failure risk analysis based on statistics becomes more and more important [1-3]. Ordinary, failure risk of underground casing pipe is affected by many factors, and shows very strong spatial variability [4, 5]. In the predictive model, both criteria weights and order weights should be considered. Since the 20th century, many progresses have been made on weights calculation, and they are applied to many domains [6-9]. Geostatistics is the core of surface analysis, and interpolating images can be worked out by geostatistical techniques for the space sample data. Spatial variability with their values and locations of space sample points can be analyzed, and interpolating surfaces can be obtained with ordinary kriging and mathematical fitting techniques [10, 11].

In this article, the spatial variability is analyzed for influence factors, and interpolating images are worked out with kriging and mathematical fitting techniques. The failure risk is calculated with predictive model, and the distribution of failure risk of underground casing pipe is investigated.

Risk Predictive Model

If the number of space points is m, i represents any one of those space points. The number of influence factors is n, and j represents any one of those factors. Here, x_{ij} is the j-th factor's value in any space point i. The failure risk is represented as R_i, then, it can be calculated as follow,

$$R_i = \sum_{j=1}^{n} \left(\frac{u_j v_j}{\sum_{j=1}^{n} u_j v_j} \right) x_{ij} \tag{1}$$

In which, u_j is criteria weight of the factor j, v_j is order weight of the factor j.

Therefore, weights of failure risk are calculated from criteria weights and order weights. Image that the same factor in different space point has the same weight. It means that criteria weights only related to influence factor, does not relate with the space location. Ordinarily, a comparison matrix A is constructed as [a_{ij}], criteria weights are written as,

$$u_j = \frac{u_j}{\sum_{i=1}^{n} \overline{u_i}} \quad i, j = 1,2, \mathbf{L}, n \tag{2}$$

$$\overline{u}_i = \sum_{j=1}^{n} \overline{a}_{ij} \quad i, j = 1,2, \mathbf{L}, n \tag{3}$$

$$\overline{a}_{ij} = \frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}} \quad i, j, k = 1,2, \mathbf{L}, n \tag{4}$$

Before the calculation of order weighs, all factors' values in any space point "*i*" need to be reordered from maximum to minimum. Order weights only relate to space location, and do not relate with the factor. The order weighs can be obtained as follow,

$$v_j = \frac{n - r_j + 1}{\sum_{l=1}^{n} (n - r_l + 1)} \quad (j, l = 1,2, \mathbf{L} n) \tag{5}$$

Eq. (5) is the basic rank order method to calculate order weights. In this method, if there are three factors, it means n equals to 3, then the biggest factor in value is treated as r_1, and equals to 1. And so on, r_2 equals to 2, and r_3 is 3. It means that the value of factors determine order weights.

Now, compute x_{ij} in Eq. (1). For any influence factor "*j*", the normalization is written as,

$$x_j = \frac{x_j - \mathrm{Min}(x_j)}{\mathrm{Max}(x_j) - \mathrm{Min}(x_j)} \tag{6}$$

And for any space point "*i*", x_{ij} is calculated from known neighbor known points, and written as,

$$x_{ij} = \sum_{l=1}^{p} l_l z_{lj} \quad l = 1,2,3 \mathbf{L}\ p \tag{7}$$

In which, z_{lj} is the value of the l-th known point, and p is the number of interpolating space points. l_l is weight of z_{lj}, according to ordinary kriging interpolation, it must meet the following conditions,

$$\sum_{l=1}^{p} l_l = 1 \quad l = 1,2,3 \mathbf{L}\ p \tag{8}$$

$$\sum_{l=1}^{p} g_{(l-m)} l_l + m = g_{(i-m)} \quad m = 1,2,3 \mathbf{L}\ p \tag{9}$$

In which, μ ***is*** Lagrange parameters, g is semivariogram. The semivariogram can be used to describe spatial variability.

Thus, we can forecast the failure risk of underground casing pipe through above calculation based on the data of influence factors.

Application Example

As an example application, three factors in J607 block are adopted. Because there are too much data, some of them are extracted as table 1.

Table 1 Extracted data of influence factors

No.	Volume of steam injection/m^3	Volume of production/m^3	Times of injection	No.	Volume of steam injection/m^3	Volume of production/m^3	Times of injection
1	26520	38253	12	60	5693	35167	3
2	30007	34015	11	61	15127	17652	9
3	16797	21368	8	62	8131	28312	4
4	26672	30291.5	12	63	18610	34785	9
5	14346	10545	8	64	13311	31625	8
6	12451	12267	6	65	18694	28158.5	9
7	13787	8970	7	66	12153	29852	7
8	19576	24437.8	12	67	16177	27424.7	8
9	27895	37101	11	68	37270	36730	17
10	21381	41022	12	69	30662	30590.9	16
11	25302	34033	17	70	53255	45458.1	15
12	14734	28380	8	71	20651	38303	10
13	14203	15330	7	72	31419	31605	17
14	14448	25255	8	73	22516	36927	10
15	13279	30264	8	74	11361	21320	7
16	20470	16574	9	75	11343	19491	6
17	14619	28477	9	76	3988	9415	3
18	16804	19708	8	77	5114	42314	4
19	35453	50579	17	78	12620	22661	6
20	20920	34308	12	79	13794	28796	8
21	29883	47441.1	13	80	12696	18464	7
22	29359	45070	13	81	17194	24411	6
23	2445	1680	2	82	11820	24300	7
24	21574	38851	12	83	13145	21364	5
25	7338.7	21764	8	84	36704	56825	14
26	19020	37101	11	85	8167	14338	5

According to the method above, spatial variability is analyzed, model fitting is fulfilled and ordinary kriging is use to create interpolating surfaces. For example, the semi-variogram image of steam injection volume is shown as Fig. 1. In semi-variogram surface images, the center is zero distance of lag, and variability increase from low to high with colors from dark blue to green.

With ordinary kriging and mathematical fitting techniques, interpolating image of steam injection volume is shown as Fig. 2.

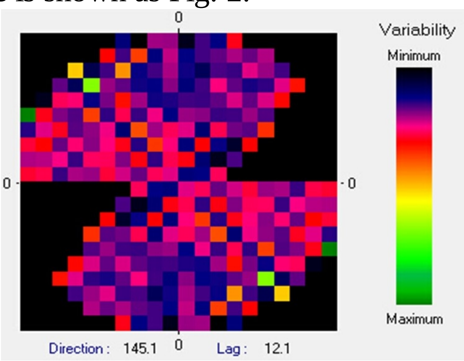

Fig. 1 Semi-variogram image

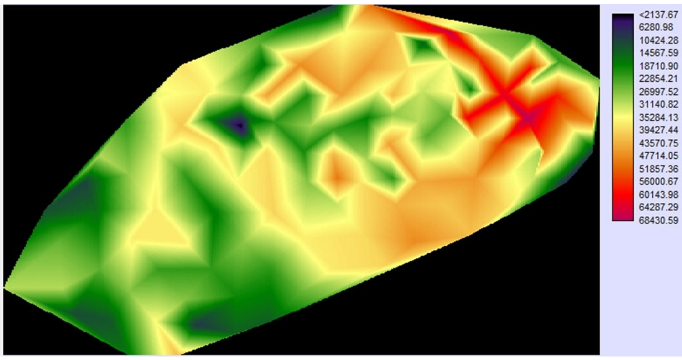

Fig. 2 Interpolating image of production volume

With the same method, the semi-variogram image and interpolating image of other two factors, times of steam injection and volume of oil production, can be obtained. Before the calculation of failure risk based on above predictive model, those imagines need to be normalized. They can be standardized with fuzzy to 0 to 255, in which 255 represents the maximum risk, and 0 represents the minimum risk. Then, the failure risk of underground casing pipe is worked out as Fig. 3.

Results Analysis and Conclusions

Through the construction of failure risk predictive model based on geostatistics, the failure risk of an application example for underground casing pipe is calculated. It can be found that the dangerous areas with more than 200 risk degree, and more attention is needed. Therefore, accurate prediction results can be obtained through this prediction model

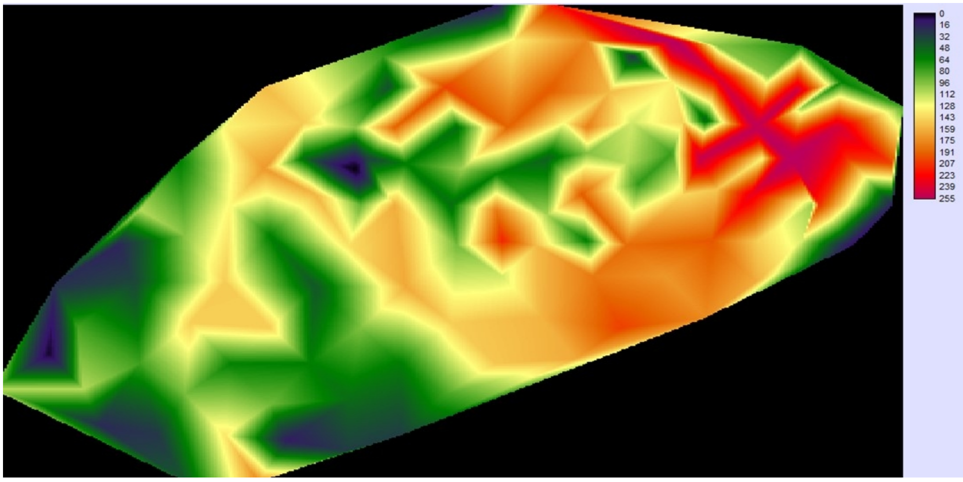

Fig. 3 Predictive result of application example

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