An attribute recognition model to predict the groundwater potential of sandstone aquifers in coal mines

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The groundwater potential prediction of sandstone aquifers is an important pre-requisite for the implementation of reasonable and effective measures to prevent mine water inrush disasters. In this study, an attribute recognition model was combined with entropy weighting to predict the groundwater potential of sandstone aquifers in coal mines. Five evaluation indices were selected to predict groundwater potential, such as sandstone thickness, sandstone lithology coefficient, flushing fluid consumption, fracture fractal dimension and fold fractal dimension. On the basis of data analysis, the groundwater potential was classified into four levels. Confidence and improved score criteria were applied to attribute recognition. The main advantages of this model are that it enables both the prediction and quantification of the groundwater potential of sandstone aquifers. The model's results were compared with those from a comprehensive geographic information system evaluation. The final model results were in good agreement with the observed results, proving that this attribute recognition model is accurate and effective for groundwater potential prediction.

Keywords. Groundwater potential; attribute recognition; confidence criterion; improved score criterion.

1. Introduction

Groundwater is recognised as one of the most valuable natural resources. It is an immensely important and dependable source of water in all climatic regions (Todd and Mays 2005). However, every coin has two sides, and groundwater can be a disaster for coal mining. When the roofs of sandstone aquifers are affected by coal mining, water inrush may occur, which poses a serious threat to coal mining operations (Wu *et al.* 2011a,b,c,

2013). Accurate analysis and prediction of groundwater potential is not only the key to the exploration and assessment of groundwater resources but also the pre-requisite to risk evaluations of mine water inrush hazards.

Remote sensing and various types of geographic information system (GIS) modelling techniques have been widely used in groundwater research (Sener *et al.* 2005; Dar *et al.* 2010, 2011; Magesh *et al.* 2012; Manap *et al.* 2013; Yeh *et al.* 2014), and other studies have applied probabilistic

models, such as multi-criteria decision analysis (Adiat *et al.* 2012), evidential belief function (Nampak *et al.* 2014; Park *et al.* 2014), frequency ratio (Oh *et al.* 2011; Razandi *et al.* 2015), random forest and maximum entropy models (Rahmati *et al.* 2016), analytic hierarchy/network processes (AHP/ANP) (Agarwal *et al.* 2013) and artificial neural network approaches (Lee *et al.* 2012), to groundwater potential mapping. However, in coal measure strata studies, the studied object is usually sandstone aquifers confined in the bedrock. It belongs to pore-fissure aquifers, which buried depth is deeper and less information can be obtained directly. Generally, the specific yield is calculated by pumping tests and used to evaluate the groundwater potential of confined aquifers. However, pumping tests are expensive and time consuming, and hydrogeological features become more complicated as the depth of mines increases (Wu *et al.* 2016); the obtained information is, thus, usually not sufficient to reveal the hydrogeological conditions. Various methods, including statistics, sedimentology and multi-field coupling, have been applied to predict the groundwater potential of aquifers. Models characterised by comprehensive evaluation using multiple factors have been widely developed, due to the high frequency of mine water inrush disasters in China. Ma *et al.* (2010) applied a grey fuzzy comprehensive evaluation to map groundwater potential. Wu *et al.* (2011a, b, c) proposed a water-richness index of five levels that couples the AHP with GIS to delineate groundwater potential zones. Liu *et al.* (2014) investigated groundwater potential predictions for a coal roof sandstone aquifer based on a probabilistic neural network. Qiu *et al.* (2016) used grey correlation analysis, fuzzy Delphi AHP and geophysical exploration to evaluate the groundwater potential of Ordovician limestone. Yin *et al.* (2018) used a geological, tectonic and lithological composition index model for the potential groundwater yield zonation of a sandstone aquifer. In addition, many geophysical exploration methods have been used to detect groundwater potential (Shi *et al.* 2009; Wu *et al.* 2010; Liu *et al.* 2010; Dhakate *et al.* 2012; Zhang 2015; Zhu *et al.* 2015; Yang *et al.* 2016).

All these approaches make important contributions to the study of groundwater potential prediction but are subject to limitations. The geological, hydrogeological and other relevant conditions are oversimplified with a single-value coefficient, which cannot reflect the complicated relationship between multiple controlling factors and the groundwater

potential. Furthermore, constraints of location and environment mean that geophysical exploration methods are not always applicable. A synthetic attribute evaluation system for groundwater potential prediction is, therefore, needed. Although attribute recognition models have been applied in many fields, including groundwater quality (Zhang *et al.* 2005), seawater quality (Zhang *et al.* 2006), urban public transit networks (Hu *et al.* 2010), soil nutrient assessment (Jiao *et al.* 2013), risk of water inrush (Zhou *et al.* 2013; Li *et al.* 2013, 2015), and assessments of rock mass blastability (Xue *et al.* 2010) and the fatalness of gas bursts in tunnels (Wen 2011), this approach has not yet been used to delineate groundwater potential. A novel application of the model is presented in this study.

2. Attribute recognition model for groundwater potential evaluation of sandstone aquifers

A comprehensive evaluation of the groundwater potential of sandstone aquifers can be summarised as a qualitative description. Attribute mathematics mainly considers the measurement problem of the qualitative descriptors and determines the relationships among them, which provides a theoretical basis for a model based on an ordered partition class and attribute recognition. The evaluation system consists of three subsystems, such as a single-index attribute measurement system, a multiple-index synthetic attribute measurement system and an attribute recognition system.

Evaluation of the groundwater potential of sandstone aquifers requires a comprehensive evaluation system. On the basis of an analysis of the relevant factors, the groundwater potential of a coal seam-confined sandstone aquifer can be identified or predicted. Assuming X is the study object space, there are n samples $(x_1, x_2, x_3, \dots, x_n)$, each with m evaluated indices $(U_1, U_2, U_3, \dots, U_m)$. If the j th evaluation index of the i th sample is x_{ij} ($1 \leq i \leq n$ and $1 \leq j \leq m$), then any one sample can be expressed in a vector $x_i = (x_{i1}, x_{i2}, x_{i3}, \dots, x_{im})$. If F is a specific attribute space on X , such as F (the grade of groundwater potential of sandstone aquifer) $= (C_1, C_2, C_3, \dots, C_K)$ and $C_1 < C_2 < C_3 < \dots < C_K$, then $C_1, C_2, C_3, \dots, C_K$ belong to the ordinal classification of attribute F . Each situation in the attribute space becomes a set of attributes that can be compared with each other. Taking the grade of groundwater potential of a sandstone aquifer

as an example, it can be divided into four levels, and meet $(C_1, C_2, C_3, C_4) = (I, II, III, IV)$. Thus, a ‘strong’ order is established to conduct a comprehensive evaluation. Every attribute set has its own attribute measure. The single-index and synthetic

$$\mu_{xij1} = \begin{cases} 1, & x_{ij} < a_{j1} - d_{j1}, \\ \frac{a_{j1} + d_{j1} - x_{ij}}{2d_{j1}}, & a_{j1} - d_{j1} \leq x_{ij} \leq a_{j1} + d_{j1}, \\ 0, & x_{ij} > a_{j1} + d_{j1}, \end{cases} \quad (3)$$

$$\mu_{xijk} = \begin{cases} 0, & x_{ij} < a_{jk-1} - d_{jk-1}, \\ \frac{x_{ij} - a_{jk-1} + d_{jk-1}}{2d_{jk-1}}, & a_{jk-1} - d_{jk-1} \leq x_{ij} \leq a_{jk-1} + d_{jk-1}, \\ 1, & a_{jk-1} + d_{jk-1} < x_{ij} < a_{jk} - d_{jk}, \\ \frac{a_{jk} + d_{jk} - x_{ij}}{2d_{jk}}, & a_{jk} - d_{jk} \leq x_{ij} \leq a_{jk} + d_{jk}, \\ 0, & x_{ij} > a_{jk} + d_{jk}, \end{cases} \quad (4)$$

$$\mu_{xijk} = \begin{cases} 0, & x_{ij} < a_{jK-1} - d_{jK-1}, \\ \frac{x_{ij} - a_{jK-1} + d_{jK-1}}{2d_{jK-1}}, & a_{jK-1} - d_{jK-1} \leq x_{ij} \leq a_{jK-1} + d_{jK-1}, \\ 1, & x_{ij} > a_{jK-1} + d_{jK-1}, \end{cases} \quad (5)$$

attribute measures are denoted by μ_{xijk} and μ_{xik} , respectively. The attribute measure is additive.

2.1 Single-index attribute measure analysis subsystem

The classification criteria for each evaluation index have been identified. The data format of the evaluation index is presented in table 1 (Li *et al.* 2013). The attribute measure of the sample value X_{ij} of the indices of U_j with attribute C_k can be expressed by $\mu_{xijk} = \mu(x_{ij} \in C_k)$ ($1 \leq k \leq K$), μ can be calculated by the attribute measure function.

In table 1, a_{jk} should satisfy $a_{j0} > a_{j1} > \dots > a_{jK}$ or $a_{j0} < a_{j1} < \dots < a_{jK}$. To construct the attribute measure functions, b_{jk} and d_{jk} are necessary. Following Li *et al.* (2013, 2015), they are defined as follows:

$$b_{jk} = \frac{a_{jk-1} + a_{jk}}{2}, \quad k = 1, 2, \dots, K, \quad (1)$$

$$d_{jk} = \min \{|b_{jk} - a_{jk}|, |b_{jk+1} - a_{jk}|\}, \quad k = 1, 2, \dots, K-1. \quad (2)$$

When $a_{j0} > a_{j1} > \dots > a_{jK}$, the single-attribute measure functions can be found in Li *et al.* (2013) and are not discussed here; when $a_{j0} < a_{j1} < \dots < a_{jK}$, the single-attribute measure function μ_{xjk} can be expressed as:

where $k = 1, 2, \dots, K-1$; $i = 1, 2, \dots, n$; $j = 1, 2, \dots, m$.

2.2 Synthetic attribute measure analysis subsystem

In the evaluation of the groundwater potential of a sandstone aquifer, the weights of all the indices should be considered. The multiple-index synthetic attribute measurement μ_{xik} can be expressed as

$$\mu_{xik} = \sum_{j=1}^m \omega_j \mu_{xijk}, \quad (6)$$

where ω_j is the weight of the evaluation index U_j .

2.3 The improved attribute recognition analysis subsystem

Attribute recognition analysis depends on the synthetic attribute measure μ_{xik} . In general, the evaluation set $(C_1, C_2, C_3, \dots, C_K)$ is an ordered set, so a confidence criterion can be adopted to discern the grade of the evaluation object.

According to the confidence criterion, if $C_1 < C_2 < C_3 < \dots < C_K$, then

$$k' = \max \left\{ k : \sum_{j=1}^m \mu_{xijk} \geq \lambda, \quad 1 \leq k \leq K \right\}. \quad (7)$$

Table 1. Grade subdivisions for single-index attribute measure.

Evaluation index	Assessment grade			
	C_1	C_2	$\dots$	C_K
U_1	$a_{10} - a_{11}$	$a_{11} - a_{12}$	$\dots$	$a_{1K-1} - a_{1K}$ or $< (>)a_{1K}$
U_2	$a_{20} - a_{21}$	$a_{21} - a_{22}$	$\dots$	$a_{2K-1} - a_{2K}$ or $< (>)a_{2K}$
$\dots$			$\dots$	
U_m	$a_{m0} - a_{m1}$	$a_{m1} - a_{m2}$	$\dots$	$a_{mK-1} - a_{mK}$ or $< (>)a_{mK}$

If $C_1 > C_2 > C_3 > \dots > C_K$, then

$$k' = \min \left\{ k : \sum_{j=1}^m \mu_{xijk} \geq \lambda, \quad 1 \leq k \leq K \right\}, \quad (8)$$

where λ is the confidence coefficient, $0.5 < \lambda < 1$. In general, λ ranges in value from 0.6 to 0.7 (Cheng 1997).

Using the above criteria, the grade of the samples can be confirmed but samples of the same grade cannot be compared. According to the attribute recognition scoring criteria, the higher the score the better the groundwater potential. The score q_{xi} can be expressed as:

$$q_{xi} = \sum_{l=1}^K n_l \mu_{xik}, \quad (9)$$

where n_l is the value of the evaluation grade, $n_l = K$; $l = 1, 2, 3, \dots, K$.

The scores of samples of different grades may have the same value, meaning that the scores of all samples are discontinuous. To solve this, the scores of samples in the same grade can be standardised separately, as follows:

$$q_{xi}^* = \frac{q_{xi} - \min(q_{xi})}{\max(q_{xi}) - \min(q_{xi})}. \quad (10)$$

Then

$$q = q_{xi}^* + K - 1, \quad (11)$$

where q_{xi}^* is the standardised value; K is the grade value of the sample, $K = 1, 2, 3, \dots$; and q is the final score of the sample.

According to the final score of the sample, the grade of groundwater potential evaluation can be divided into K levels and meet I (0–1), II (1–2), III (2–3), $\dots$

2.4 Entropy weight analysis of the evaluation indices

The approach for obtaining constant weights can be divided into subjective and objective weights. Entropy weight, which is one of the objective weights, was used in this study. The entropy weights describe the importance of the evaluation index. The smaller the entropy value, the more information the evaluation index provides; thus, the more important the evaluation index, the larger the entropy weight (Wu *et al.* 2011a, b, c). The specific steps involved in entropy weight are as follows:

- (1) Because the units and magnitudes of the evaluation indices differ, the zero-centred method is used to standardise the values of each index:

$$y'_{ij} = \frac{x_{ij} - \text{ave}(x_j)}{s_j}, \quad (12)$$

where y'_{ij} is the standardised value, x_{ij} is the evaluation index value of the sample, $\text{ave}(x_j)$ is the average value of the j th evaluation index and s_j is the standard deviation of the j th evaluation index, $1 \leq i \leq n$ and $1 \leq j \leq m$.

- (2) Negative values may arise after standardisation. According to Shannon entropy theory, the weight depends on the variation degree among the characteristic values of the evaluation indices, so the effect of negative values can be eliminated by coordinate translation:

$$y_{ij} = y'_{ij} + t, \quad (13)$$

where y_{ij} is the value after coordinate translation and t is the coordinate translation value (in this study, $t = 5$).

- (3) According to the concept of entropy, assuming there are n samples and m evaluation criteria, entropy can be defined as:

Figure 1. Location of the study area.

$$H_j = -\frac{1}{\ln n} \left(\sum_{i=1}^n f_{ij} \ln f_{ij} \right), \quad (14)$$

$$f_{ij} = \frac{y_{ij}}{\sum_{i=1}^n y_{ij}}, \quad i = 1, 2, \dots, n; \quad j = 1, 2, \dots, m. \quad (15)$$

- (4) Weight ω_j can be calculated using the following formula:

$$\omega_j = \frac{1 - H_j}{m - \sum_{j=1}^m H_j}, \quad \omega = (\omega_j)_{1 \times m}, \quad \sum_{j=1}^m \omega_j = 1. \quad (16)$$

3. Study area

3.1 Geological background

This study focused on the Maiduoshan coal mine in the western part of the Ningdong coalfield, Yinchuan, Ningxia province, China (figure 1). The coal is of the Jurassic Yan'an Formation, and the main mineable coal seam is seam No. 2. On the basis of drilling data, the main aquifer is the pore-fissure-confined aquifer in the sandstone between the lower Zhiluo Formation and the roof of the No. 2 coal seam. The groundwater potential of the sandstone aquifer at the maximum height of the interconnected fractures zone (Wei *et al.* 2017) was the research object of this study.

3.2 The evaluation indices and grade standards

The regularity and distribution of groundwater potential in a sandstone aquifer is influenced by many factors. On the basis of geological and hydrogeological conditions, five evaluation indices were selected, such as sandstone thickness (U_1), sandstone lithology coefficient (U_2), flushing fluid consumption (U_3), fault fractal dimension (U_4) and fold fractal dimension (U_5).

- (1) U_1 , sandstone thickness, is an important indicator in the evaluation of groundwater potential. When other factors are certain, the larger the sandstone thickness, the greater the water content of the aquifer per unit thickness, and the greater the groundwater potential. In general, sandstone thickness refers to the thickness of brittle rock, including fine sandstone, medium sandstone, coarse sandstone and conglomerate.
- (2) U_2 , the sandstone lithology coefficient, is the proportion of sandstone in the target aquifer, and it reflects the lithology condition of the coal seam roof in the evaluation of groundwater potential. The larger the sandstone lithology coefficient, the larger the relative value of sandstone thickness, and the better the groundwater potential.
- (3) U_3 , flushing fluid consumption, is used because the storage of groundwater in sandstone aquifers is inhomogeneous and depends on the distribution of pores and fissures. The flushing fluid consumption during drilling is measured by pumping drilling mud into the borehole.

Table 2. Index values for the first 20 samples evaluated for groundwater potential in the study area.

Sample no.	Borehole	Sandstone thickness (m)	Sandstone lithology coefficient	Flushing fluid consumption ($\text{m}^3 \text{h}^{-1}$)	Fault fractal dimension	Fold fractal dimension
1	405	122.120	0.924	1.607	0.170	0.850
2	407	77.390	0.913	5.614	0.950	0.150
3	601	126.490	0.924	1.298	0.970	0.000
4	603	63.380	0.791	5.442	0.350	0.710
5	605	116.220	0.918	5.633	0.025	0.450
6	606	90.150	0.931	1.012	0.750	0.750
7	802	50.000	0.606	0.512	0.750	0.030
8	803	71.400	0.831	2.265	0.000	0.550
9	804	96.560	0.885	0.133	0.000	0.770
10	805	73.660	0.912	0.304	0.000	0.500
11	806	93.770	0.955	0.100	0.100	0.820
12	807	46.640	0.775	1.000	0.990	0.320
13	902	76.460	0.936	1.089	0.350	0.210
14	903	61.500	0.643	1.288	0.040	0.680
15	904	91.410	0.950	0.316	0.000	0.850
16	905	98.550	0.964	3.476	0.000	0.300
17	1002	104.180	0.831	1.401	0.550	0.420
18	1003	124.240	0.934	1.619	0.125	0.870
19	1004	100.940	0.989	4.221	0.000	0.770
20	1005	81.850	0.932	2.219	0.000	0.260

Figure 2. Frequency histograms of the evaluation indices.

Table 3. Indices and grading standards for groundwater potential evaluation in the study area.

Evaluation index	Grade of groundwater potential			
	I (C_1)	II (C_2)	III (C_3)	IV (C_4)
Sandstone thickness (m)	0–90	90–120	120–150	>150
Sandstone lithology coefficient	0–0.8	0.8–0.85	0.85–0.9	0.9–1
Flushing fluid consumption ($\text{m}^3 \text{h}^{-1}$)	0–1	1–2.5	2.5–3.5	>3.5
Fault fractal dimension	0–0.5	0.5–0.8	0.8–1.1	>1.1
Fold fractal dimension	0–0.3	0.3–0.5	0.5–1	>1

Table 4. Entropy weights of evaluated indices.

Evaluated index	Sandstone thickness	Sandstone lithology coefficient	Flushing fluid consumption	Fault fractal dimension	Fold fractal dimension
Entropy weight	0.1935	0.2407	0.1768	0.1927	0.1963

Table 5. Evaluations of groundwater potential for the first 20 samples in the study area.

Sample no.	Borehole	Synthetic attribute measures				Attribute recognition		
		C_1	C_2	C_3	C_4	Confidence criterion ($\lambda = 0.65$)	Score criterion (q_{xi})	Final score (q)
1	405	0.193	0.260	0.271	0.276	III	2.631	2.561
2	407	0.374	0.015	0.248	0.362	IV	2.598	3.186
3	601	0.232	0.196	0.322	0.250	III	2.590	2.531
4	603	0.551	0.076	0.196	0.177	III	1.999	2.089
5	605	0.193	0.268	0.156	0.383	IV	2.729	3.285
6	606	0.182	0.317	0.261	0.241	III	2.560	2.508
7	802	0.805	0.131	0.064	0.000	I	1.259	0.000
8	803	0.386	0.390	0.224	0.000	II	1.838	1.404
9	804	0.424	0.139	0.380	0.057	III	2.070	2.142
10	805	0.563	0.098	0.162	0.176	II	1.952	1.608
11	806	0.442	0.121	0.169	0.268	III	2.263	2.286
12	807	0.601	0.206	0.167	0.026	II	1.617	1.011
13	902	0.636	0.123	0.000	0.241	II	1.845	1.418
14	903	0.664	0.139	0.196	0.000	I	1.532	1.000
15	904	0.457	0.106	0.157	0.280	III	2.260	2.284
16	905	0.332	0.250	0.093	0.325	III	2.410	2.396
17	1002	0.087	0.866	0.047	0.000	II	1.961	1.623
18	1003	0.193	0.246	0.273	0.288	III	2.656	2.580
19	1004	0.219	0.167	0.188	0.425	IV	2.820	3.353
20	1005	0.479	0.241	0.039	0.241	II	2.041	1.766

Because the level of flushing fluid consumption directly reflects the development of pores and fissures, the degree of groundwater potential rises in line with this value.

- (4) U_4 , fault fractal dimension, and U_5 , fold fractal dimension, reflect structural complexity. A damaged rock mass with a large number of fractures is a good place for groundwater

storage (Acharya *et al.* 2014). The more complex the geological structure, the more developed the fractures, and the better the groundwater potential. Geological structural complexity can be quantified by the fractal dimensions of faults and folds, which are synthetic indices that characterise scale, number and dynamic mechanism (Wang *et al.* 2016).

Figure 3. Groundwater potential map produced by the attribute recognition model.

There were 116 samples in the study area. The first 20 samples were taken as an example, presented in table 2. According to a statistical analysis of data for the study area (figure 2), the evaluation indices were classified into four grades. The grading standards for the evaluation indices are presented in table 3. The grade of groundwater potential is level I < level II < level III < level IV.

3.3 Evaluation of the groundwater potential of a sandstone aquifer

On the basis of the values presented in table 3, single-index attribute measures were computed using equations (1–5), multiple-index synthetic attribute measures were calculated using equation (6) and the weights of the evaluated indices were

Figure 4. Groundwater potential map produced by the GIS method.

calculated using equations (12–16) as presented in table 4.

On the basis of the obtained synthetic attribute measures, the grades of groundwater potential of the samples were obtained using equation (7); λ was assumed to be 0.65 in the present study. To quantify the qualitative results, the score criterion was used and the sample scores (q_{xi}) were calculated using equation (9). After data processing, the

final scores for the samples (q) were obtained by using equations (10 and 11). The evaluations of groundwater potential are presented in table 5.

3.4 The mapping of groundwater potential and results analysis

On the basis of the predicted results, the groundwater potential of the study area can be

classified into four levels and meet the criteria for grades I (0–1), II (1–2), III (2–3) and IV (3–4), shown in figure 3. As figure 3 shows, the groundwater potential across a wide area is level III, level IV areas are mainly located on both sides of the fault concentrated zone, level II areas are mainly located in the north and south ends of the study area, and level I areas are smaller and mainly located around a few boreholes.

To verify the accuracy of the presented method, the predicted results were compared with the results of multi-factor information fusion based on GIS. The results for the same indices and weights are shown in figure 4. The results of the two models are very similar. The observed result around drain borehole of FS reveals a maximum water inrush rate from the borehole of $350 \text{ m}^3 \text{ h}^{-1}$, which means that the presented method provides an easier and more powerful tool for systematic prediction of the groundwater potential map of a sandstone aquifer.

4. Conclusions

Determining the groundwater potential of an aquifer is a spatial problem that requires data from different sources (Adiat *et al.* 2012). Due to the heterogeneous nature of aquifers, the spatial distribution of groundwater is discontinuous and stochastic. On the basis of the analysis of lithology and geological structural characteristics, five important indices (sandstone thickness, sandstone lithology coefficient, flushing fluid consumption, fault fractal dimension and fold fractal dimension) were selected. A four-level grading classification was identified based on a histogram analysis of all the data samples. A synthetic attribute evaluation system, combining attribute mathematical theory and entropy weights, was proposed to evaluate the groundwater potential of the aquifer. The main advantage of the presented model is that the application of two criteria allows not only the predictive mapping of favourable zones for groundwater occurrence but also allows the groundwater potential of sandstone aquifers to be quantified.

To check the validity and accuracy of the attribute recognition model, field-observed results were checked. The results of a well-known GIS model combined with the same indices and weights were compared with the presented results, which revealed good agreement. In addition, the

groundwater potential was evaluated with the measured data, which not only reduces the influence of subjective factors but also improves the accuracy of the model.

In summary, the attribute recognition model results indicate that this model can successfully be applied in groundwater potential of sandstone layers prediction. The proposed method provides rapid, accurate and cost-effective results, which will hopefully result in the future avoidance of mining disasters.

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