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Study on an Intelligent Inference Engine in Early-Warning System of Dam Health

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Abstract With systems engineering and artificial intelligent methods, an early-warning system of dam health (EWSDH) is developed. This system consists of integration control module, intelligent inference engine (IIE), support base cluster, information management and input/output modules. As a central processing unit of EWSDH, IIE is a decision support system for monitoring the operation characteristics and diagnosing unexpected behaviour of dam health. With the time-frequency domain localization properties and self-learning ability of wavelet networks based on wavelet frames, IIE builds some new monitoring models of dam health. The models are used to approximate and forecast the operation characteristics of dam. The methods of attributions reduction in rough sets theory are presented to diagnose adaptively the unexpected behaviour. The proposed system has been used to monitor dam health successfully.

Keywords Dam health · Early-warning system · Inference engine · Intelligent methods

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1 Introduction

Dam construction has developed very fast in China since 1950. There are now 17,526 dams 15–30 m high and 4,578 dams exceeding 30 m. These projects bring huge benefits in flood control, irrigation, power generation. However, hidden troubles exist in some dams due to hydrology, geology, design, construction and aging. Providing the necessary guarantees of health for all dams is an essential topic. There is no structure whose strength and integrity could be guaranteed under any conditions of operation. Monitoring health in a set of hydrotechnical structures being in service can be based on a group of diagnostic parameters. The measurement and analysis of them gives prompt decisions on the diagnosis of the state (Gaziev 2000; Peyras et al. 2006). The term early-warning system applies to an artificial system that uses the latest computing technologies to accumulate and interpret knowledge, experience, theory and method in a certain area. An early-warning system is a software system for taking decisions installed in a computer and used to resolve problems over factual data and employ heuristic techniques with the accumulated knowledge.

It is necessary and important to develop the systems to monitor dam health. The systems are used to implement the information management, real-time analysis and reasonable diagnosis for dam health. Based on prototype observations, the conventional systems solve above problems with the mathematical and mechanical methods. For example, the methods of time serial and multiple regression are adopted to build monitoring models. Finite element method (for short FEM) is used to implement the structural calculation and find out the geneses of abnormal cases. However, these classical methods lay usually no strong emphasis on the learning of experiences and expert knowledge (Marengo 2000; Crepon 1999; Wu and Su 2005). Based on systems engineering and artificial intelligent methods, an early-warning system of dam health (for short EWSDH) is developed to realize above aims.

This paper is organized as follows. The global structure of EWSDH is presented in Section 2. An intelligent inference engine (for short IIE) is built in Section 3. IIE is an information mining tool that tries to derive answers on dam behavior from prototype observations, other similar dam engineering and expert knowledge. It can be used to find meaningful relationships between physical quantities and exploit this information in modeling and simulation. If the dada signifies critical or abnormal situations, IIE can explain such critical situations. Discovering long term and non-obvious trends in data is also an important information mining result. The monitoring models based on wavelet network are proposed to analyze prototype observations. The IIE builds a diagnosis model of abnormal cases with rough sets theory. In Section 4, the proposed system is used to monitor one concrete dam. Section 5 summaries the main conclusions reached in this work.

2 Global Structure of EWSDH

The system is consisted of integration control module, intelligent inference engine, support base cluster, information management and input/output modules. Its global structure is shown as Fig. 1.

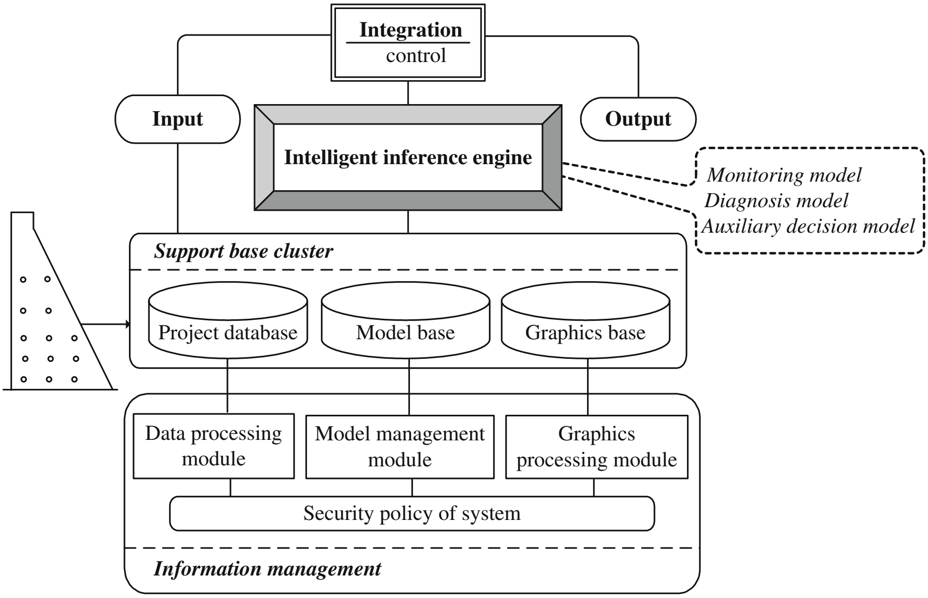


Fig. 1 Global structure of EWSDH

2.1 Integration Control

The integration control module is a multilevel control menu. It can harmonize intelligent inference engine, support base cluster, information management and input/output modules.

2.2 Support Base Cluster

Support base cluster is composed of project database, model base, graphics base.

2.2.1 Project Database

The project database is used to store the large number of project archives and observing data. According to the property and source of data, the project database is divided into four sub-databases, named project archive database, origin database, reorganization database and generation database, respectively. The project archive database mainly stores the design, construction and operation data on health monitoring. The origin database stores prototype observations collected by observation system. The reorganization database stores the processed data. The generation database mainly stores all kinds of results obtained from intelligent inference engine.

2.2.2 Model Base

The base mainly includes the analysis programs of observed data, structure analysis programs, seepage analysis programs, diagnosis programs etc. By use of these programs, the system can establish the monitoring models, check the strength and stability. When the unexpected behaviour occurs, they can be used to implement all kinds of numerical analysis.

2.2.3 Graphics Base

The graphics base mainly includes the figures and tables for project health, observation data analysis, structure and seepage analysis, comprehensive diagnosis and auxiliary decision etc.

2.3 Intelligent Inference Engine

As the central processing unit of EWSDH, IIE is an aggregate of knowledge and expert experience. It carries out the integration and analysis of health information, diagnoses dam health, and makes decisions. By use of the judgment criterion (usually monitoring model), IIE can distinguish the property of every observation, viz. normal, basic normal or doubtful. If the observation value is a doubtful point, it will continue the genesis analysis. Firstly, it will check the observation system. If the doubtful point is caused by the observation fault, this system will send an alarm and warn the operators to repair the observation system. The inference is over. If not, diagnosis model is started. If the genesis is found out, the inference is over. If the

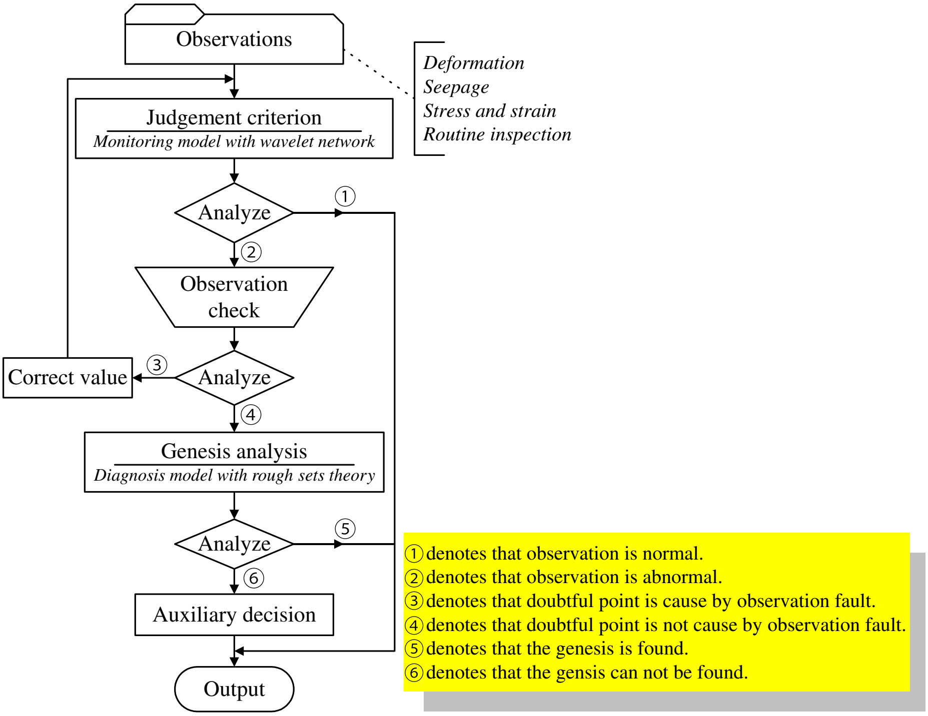


Fig. 2 Work flowchart of intelligent inference engine

genesis is not found, the system enters into the module of auxiliary decision. The inference flow is shown in Fig. 2.

3 Intelligent Inference Engine

3.1 Monitoring Model of Dam Health Based on Wavelet Network

For a wavelet network based on wavelet frames, wavelet basis functions replace hidden node functions of conventional feed-forward neural network of single hidden layer, the dilation parameters and translation parameters replace connection weights from input layer to hidden layer and the thresholds of hidden layer, respectively. It integrates the time-frequency domain localization properties of wavelet frames and self-learning ability of feed-forward neural networks. Therefore the wavelet network has strong ability of fit and tolerating fault, and is a powerful tool for function approximation (Aussen and Murtagh 1997; Fournier 2003; Liu et al. 2003). IIE adopts wavelet networks based on wavelet frames to build the monitoring models. The models can approximate and forecast operation characteristic of dams. The loads of dams are regarded as the wavelet network inputs. Observed effects of dams are as the network outputs. The network is trained to adequate precision with large numbers of forecast samples. Consequently this network can denote the nonlinear relation between loads and effects of dams, thereby monitor dam health.

3.1.1 Wavelet Frames

Assume that a wavelet function $\psi(x) \in L^2(R)$, let

$$\psi_{mn}(x) = a^{\frac{n}{2}} \psi\left(a^n x - mb\right), \ m, \ n \in Z \tag{1}$$

where $a > 1$ is dilation parameter, $b > 0$ is translation parameter. If ψ satisfies an appropriate decay condition in time-frequency domain, then there exist constants $a_0 > 1$ and $b_0 > 0$ such that, for any $a \in (1, a_0]$ and $b \in (0, b_0]$, $\{\psi_{mn}(x)\}$ constitutes a frame for $L^2(R)$. $\{\psi_{mn}(x)\}$ is also named wavelet frame made by ψ.

Given a wavelet function $\psi(x) \in L^2(R^d)$, define

$$\psi_{mn}(x) = a^{\frac{1}{2}nd} \psi\left(a^n x - mb\right), \ n \in Z, m \in Z^d \tag{2}$$

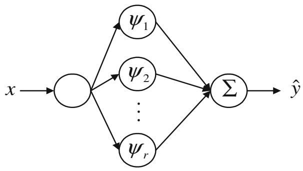
where dilation parameter $a > 1$ and translation parameter $b > 0$. As in the one-dimensional case, if ψ itself is localized in time and in frequency, there exist constants $a_0 > 1$ and $b_0 > 0$ such that, for any $a \in (1, a_0]$ and $b \in (0, b_0]$, $\{\psi_{mn}(x)\}$ forms a frame for $L^2(R^d)$. $\{\psi_{mn}(x)\}$ is also called multidimensional wavelet frame.

3.1.2 Wavelet Network Structure Based on Wavelet Frames

The wavelet network structure can be described in Fig. 3. It can implement the mapping of $R^d \to R$

$$\hat{y} = \sum_{k=1}^{r} w_k \psi_k(x) \tag{3}$$

Fig. 3 Wavelet network structure



where $x = (x_1, x_2, ..., x_d) \in R^d$ is the input vector of wavelet network, namely load set of dams, $\hat{y}$ is the output of wavelet network, namely calculated value by the monitoring model of dam health, $\psi_k(x)$, $1 \leq k \leq r$, are the basis wavelet neurons chosen from a given wavelet frame $\psi_{mn}(x)$, w_k, $1 \leq k \leq r$, are the weights of wavelet network from hidden layer to output layer, r is the number of hidden layer nodes of the network.

3.1.3 Learning Algorithm of Wavelet Network

The dilation parameters and translation parameters of the wavelet network described in Fig. 3 can be obtained by the time-frequency analysis of trained data. This system determines the unknown weight coefficients with the forgetting factors method (Benedetto and Heinig 2003; Enns and Si 2002; Razavi and Araghinejad 2009).

Let $\Psi_t = [\psi_1(t), \psi_2(t), ..., \psi_r(t)]^T$, $W_t = [w_1(t), w_2(t), ..., w_r(t)]^T$, then Eq. 3 can also be expressed

$$\hat{y} = \sum_{k=1}^{r} w_k \psi_k(x)\alpha + \Psi_t^T W_t \tag{4}$$

where $\psi_k(t)$, $w_k(t)$ is the input and weight of No. k wavelet neuron in time t, respectively, T denotes matrix transposed. To obtain recursively the network weights, forgetting factors method can be described as follows

$$\left.\begin{aligned} W_t &= W_{t-1} + K_t\left[y_t - \Psi_t^T W_{t-1}\right] \\ K_t &= \left(\alpha + \Psi_t^T P_{t-1}\Psi_t\right)^{-1} P_{t-1}\Psi_t \\ P_t &= \left[P_{t-1} - K_t\Psi_t^T P_{t-1}\right]/\alpha \end{aligned}\right\} \tag{5}$$

where α is forgetting factor, and $0 < \alpha \leq 1$.

3.1.4 Criteria Evaluating Dam Behavior

Dam behavior can be assessed at any time by use of above built models. Assume that $\Delta\delta$ is the difference between observation and calculation of above model, S is bias error of identification model. If $2S \leq \Delta\delta < 3S$, trail monitoring is requested and the genesis need be analyzed when trend variation occurs. If $|\Delta\delta| \geq 3S$, dam behavior is abnormal.

3.2 Diagnosis Model of Abnormal Behaviour Based on Rough Sets Theory

The relation between load set and effect set is a main factor determining characteristics of dam structure. So the diagnosis of abnormal behaviour is a process of discovering knowledge on the logic patterns between unexpected behaviour and its geneses. Rough sets theory is a new mathematical tool. It can be employed to handle imprecise, uncertain or incomplete descriptions (Lian 2000). In less than two decades, it has rapidly established itself in many real-life applications such as medical diagnosis, control algorithm acquisition and process control, information retrieval and structural engineering (Barbagallo et al. 2006; Luo and Shao 2003; Su et al. 2003; Swiniarski and Hargis 2001). IEE uses rough sets theory to mine adaptively the pattern between abnormal behaviour and geneses. Its mechanism can be depicted as Fig. 4.

(1) *Build anamnesis base of dam.* Firstly, the condition attributes (possible geneses) and decision attributes (abnormal behaviour of dam) are obtained according to field knowledge and experiential knowledge. Secondly, the anamnesis base of dam is built by collecting and handling data about dam health.
(2) *Discriminate value of attribute.* There are two types of attribute values in the decision table of diagnosing unexpected behaviour. One is continuous attribute such as deformation and temperature, which describes dam genesis to be observed. Its value is in one continuous universe. Other is represented by language or some discriminative value such as crack, casting method and maintenance effort of concrete. The attribute value needs to be described by discriminative data when the decision table of diagnosing dam unexpected behaviour is analyzed with rough sets theory. The continuous value needs to be discriminated. The discriminative value is abstracted. So the decision system of diagnosing dam unexpected behaviour is built. It is called information system (S). Information system can be viewed as a decision table. Its rows and columns correspond to an anamnesis of dam (objects) and attributes, respectively.

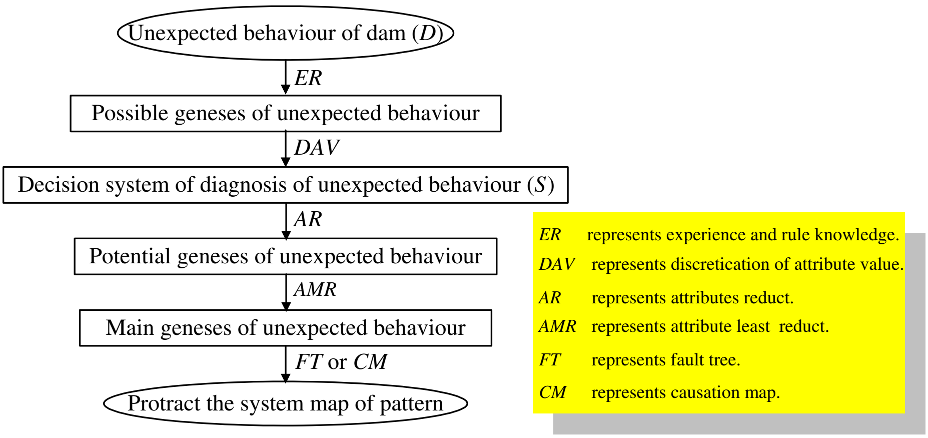


Fig. 4 Mechanism of adaptive diagnosis model on abnormal behaviour of dam

A decision table (S) with 4-tuple can be represented as follows

$$S = (U, R, V, f) = (U, C \cup D, V, f) \tag{6}$$

where U is the universe which consists of a finite set of objects, $U = \{x_1, x_2, ..., x_n\}$, $R = C \cup D$ is a finite set of attributes, C denotes the *condition attribute*, and D represents the *decision attribute*, $C = \{c_1, c_2, ..., c_m\}$, $D \neq \phi$, $V = \bigcup_{a \in R} V_a$, V_a is a domain of the attribute $a \in C \cup D$, $f{:}U \times (C \cup D) \to V$ is the information function such that $f(x, a) \in V_a$ for every $x \in U$ and $a \in C \cup D$ and any pair (a, v), $a \in C \cup D$, $v \in V_a$ is called a *descriptor* in S.

In the decision table, some condition attributes are not logical related with decision attributes, or some condition attributes have same effect to decision attributes. Hence, redundant attributes in condition attribute set (C) need be eliminated.

(3) *Reduce attributes.* Based on keeping logic relation between dam unexpected behaviour and geneses, attributes are reduced. Redundant attributes are eliminated. Potential geneses are found. This process is called mining potential geneses of dam.

The algorithm of "*D-reduct* of C" family is as follows.

Step 1. Gain *B-indiscernibility* relation. Given two finite, non-empty sets U and A, where U is the universe, and A, a set of attributes, for every attribute $a \in A$, it is possible to associate with it a set of values known as the domain of a. Any subset P of A that defines a binary relation $I(P)$ on A, which is an indiscernibility relation, can be expressed as follows.

$$xI(P)y \text{ if and only if } a(x) = a(y) \text{ for every } a \in A(7) \tag{7}$$

where $a(x)$ and $a(y)$ denote the value of attribute a for elements x and y, respectively.
Assume that R is a family of equivalence relations. If $B \subseteq R$ and $B \neq \phi$, then $\cap B$ (the intersection of all the equivalence relations belonging to B) is demoted as ind(B). $ind(B)$ represents an equivalence relation. The equivalence relation is knowledge of logical relation between condition attribute and decision attribute when data in the decision table can reflect the universe.

Step 2. Gain *positive region*. Let $B \subseteq R$, $X \subseteq U$. The "B *positive region of* X" denoted by $POS_B(X)$ is a set of objects of U, which can be properly classified to the classes of X by employing the knowledge expressed by the classification B. The "B *positive region of* X" can be expressed as follows:

$$POS_B(X) = \{x \in U \mid [x]_{ind(B)} \subseteq X\} \tag{8}$$

Step 3. Reduce redundant attributes. Let R be an equivalence relation on universe U. $r \in R$ is said to be "$r - omissible\ in\ R$", if and only if

$$ind(R) = ind(R - \{r\}) \tag{9}$$

Otherwise, r is "$r - omissible\ in\ R$". If every r in R is "$r - inomissible\ in\ R$", then R is independent.

Assume that S is the "*D-independent*" subfamily of C. $S \subset C$ is said to be "*D-reduct* of C", if and only if

$$POS_S(D) = POS_C(D) \tag{10}$$

The condition attribute set C often has many "*D-reduct*". $red_D(C)$ is said to be "*D-reduct* of C" family. All logical relations between condition attributes and decision attributes are in $red_D(C)$.

(4) *Reduce least attributes.* Main geneses are abstracted. This process is called abstracting main geneses of dam unexpected behaviour.

Many groups of logical relations between condition attributes and decision attributes may be found. The amount of condition attributes is different in each group of logical relation between condition attributes and decision attributes. "*D-least reduct* of C" need to be gained. It is the principle of abstracting "*D-least reduct* of C" that the amount of chosen attributes is least and the amount of equivalence relations is least. The algorithm of abstracting "*D-least reduct* of C" is as follows.

Step 1. Gain *core*. The "$D - core\ of\ C$" is the set of all in dispensable relations in C and is denoted by $core_D(C)$. $core_D(C)$ can be calculated as follows.

(a) Let $X = \phi$, $Y = C$.
(b) For every $r \in Y$, calculate $POS_C(D)$ and $POS_{C-r}(D)$ with Eq. 8.
(c) If $POS_C(D) \neq POS_{C-\{r\}}(D)$, then let $X = X \bigcup \{r\}$.
(d) Let $Y = Y - \{r\}$.
(e) If $Y \in \phi$, then go to (b).
(f) Let $core_D(C) = X$.

Step 2. Gain *least reduct*. "$D - least\ reduct\ of\ C$" is denoted by $mred_D(C)$. $mred_D(C)$ can be calculated as follows.

① Let $X = core_D(C)$, $L = C - X = a1, a2, \cdots, a_m$. $T(L)$ represents L power set. $T_i(L)(i = 1, 2, \cdots, m)$ represents i steps power subset of L.
② If $POS_X(D) \neq POS_C(D)$, then let $mred_D(C) = X$ and go to ⑩.
③ Let $i = 1$, $flag = 0$.
④ Let $Y = T_i(L)$.
⑤ For every $y \in Y$, $A = X \bigcup Y$, if $POS_A(D) \neq POS_C(D)$, then
If $flag = 0$, then let $Z = A$, $flag = 1$.
If $flag \neq 0$, $card(U \mid Z) > card(U \mid$ ă$A)$, then let $Z = A$.
⑥ Let $Y = Y - y$.
⑦ If $Y \neq \phi$, then go to ⑤.
⑧ If $flag = 1$, then let $mred_D(C) = Z$ and go to ⑩.
⑨ Let $i = i + 1$. If $i \leq m$, then go to ④.
⑩ End.

(5) *Protract the system map of patterns between dam unexpected behaviour and geneses.* Based on logic relations between dam unexpected behaviour and geneses, the system map of patterns between dam unexpected behaviour and geneses are constructed with system engineering method such as fault tree and causation map.

4 Applications

As an example, the system is used to monitor one arch dam.

4.1 Introduction of One Arch Dam

The concrete arch dam, shown in Figs. 5 and 6, has a maximum height of 76.3 m and a crest length of 419 m. The crest width is 8 m and the maximum base width is 53.2 m. It is composed of 28 dam sections.

The construction of this dam was divided into three phases: 1959–1962, 1969–1972, 1978. The elevation of dam crest reaches 105.0 m, 125.0 m and 126.3 m, respectively. A continuous crack of 300 m length, shown in Fig. 7, has been observed along the elevation of 105 m from No.5 dam section to No.28 dam section. The crack depth is more than 5 m. Sixteen crack meters (Fig. 8) are installed on the above crack to monitor the crack behavior.

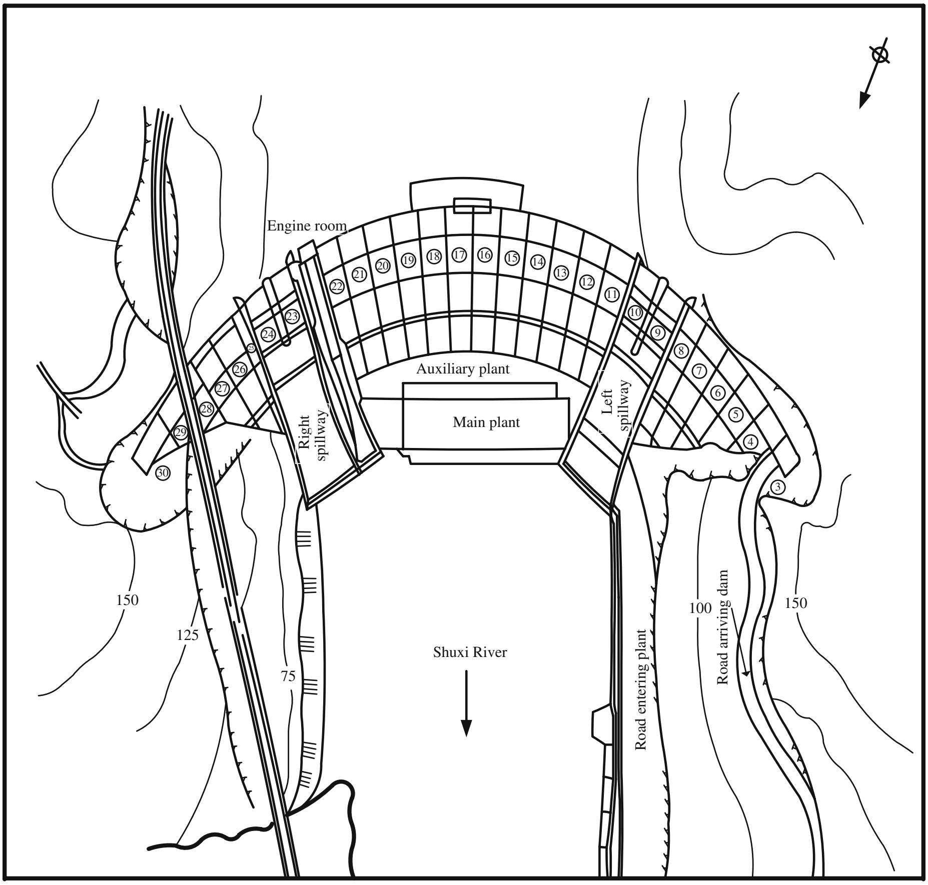


Fig. 5 Layout of one arch dam

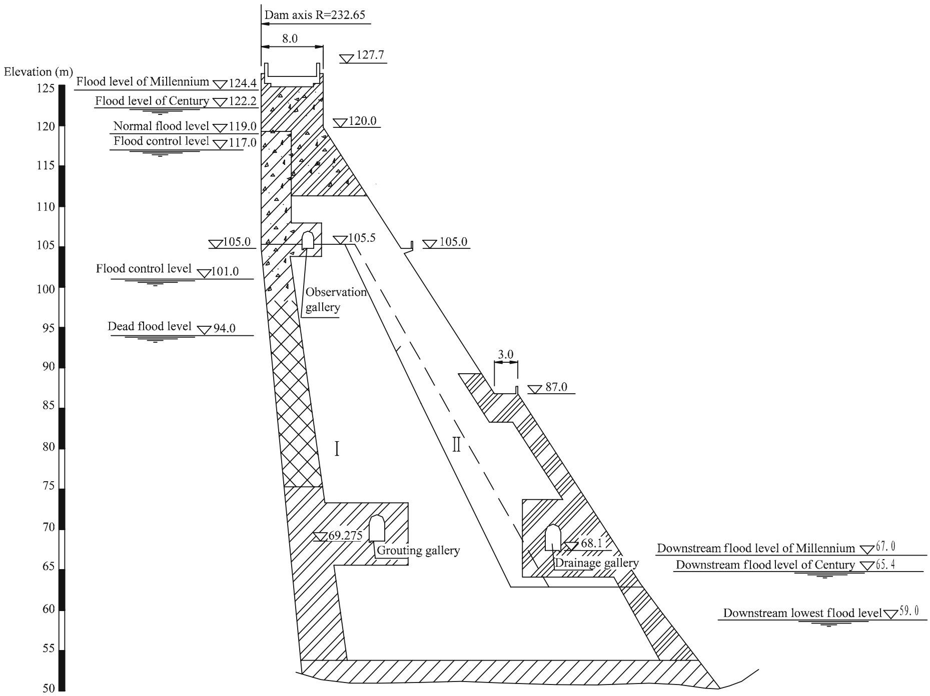


Fig. 6 Layout of one dam section

4.2 Analyze Characteristics of Dam Crack with Monitoring Model

As an example, the observed data of JS18-1 in No. 18 dam section are analyzed with the proposed method and conventional regression model, respectively. Observed data are collected from Jan, 1994 to Aug, 2008. Data from Jan, 1994 to July, 2007 are used to build the models, and data in Aug, 2007 and Aug, 2008 are used to test the forecast ability of above models. Figures 9 and 10 shows the observed environment.

Mexico hat wavelets following are chosen as hidden node functions of wavelet network.

$$\psi(x) = \left(1 - x^2\right)\exp\left(1 - x^2/2\right) \tag{11}$$

The number of influence factors is regarded as the number of input layer nodes. They are that the water level factors are H, H^2, H^3, temperature factors are $\sin\frac{2\pi t}{365}$,

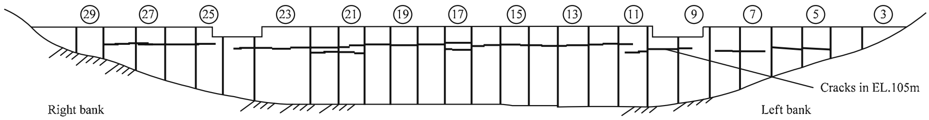


Fig. 7 Crack sketch along the downstream of arch dam

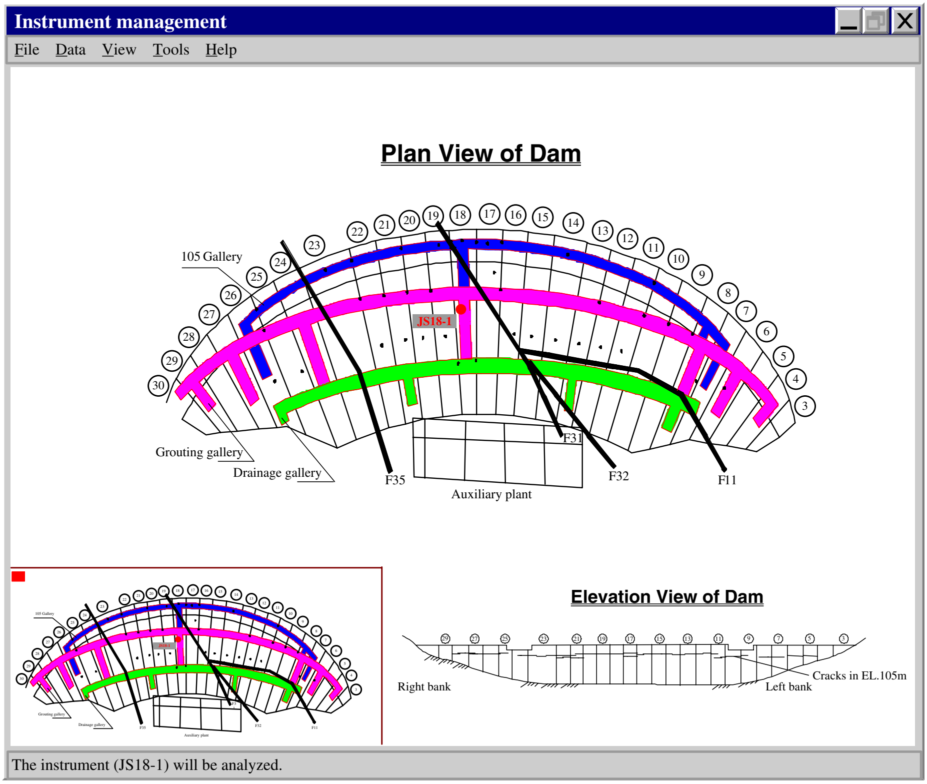


Fig. 8 Instrumented crack meters

$\sin \frac{4\pi t}{365}$, $\cos \frac{2\pi t}{365}$, $\cos \frac{2\pi t}{365}$, and θ, $\ln\theta$ are time effect factors. The number of output layer nodes is 1, namely displacement variable number. The end condition training wavelet network is that $\varepsilon = 0.001$. The system plots in Fig. 9 the process lines of approximation values and errors of dam crack with the monitoring model of the wavelet network.

For the evaluation of approximation precision, the system adopts the following regression model.

$$\delta = a_0 + \sum_{i=1}^{3} a_i \left(H^i - H_0^i\right) + \sum_{j=1}^{2} \left[b_{1j} \left(\sin \frac{2\pi jt}{365} - \sin \frac{2\pi jt_0}{365} \right) + b_{2j} \left(\cos \frac{2\pi jt}{365} - \cos \frac{2\pi jt_0}{365} \right) \right] + c_1 (\theta - \theta_0) + c_2 (\ln\theta - \ln\theta_0) \tag{12}$$

where δ is the calculated value of crack with the regression model, H is the water depth of dam upstream, namely the water level minus elevation of dam base, H_0 is

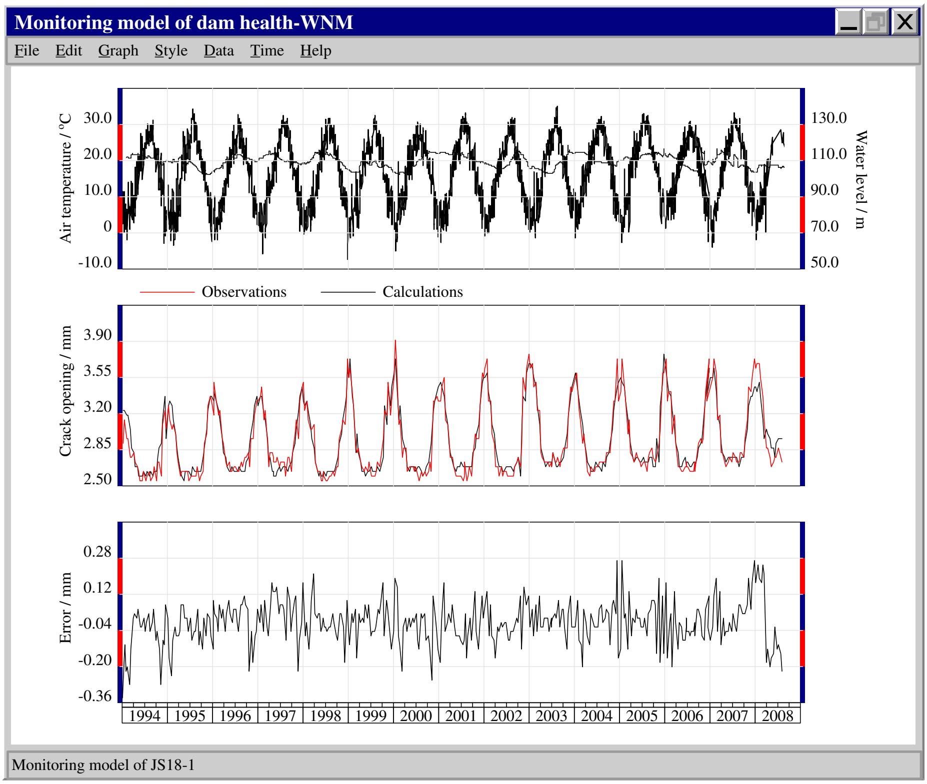


Fig. 9 Process lines of observations, approximations and errors of the proposed model

the initial water depth, t is the accumulative total number of days from the starting day to observation day, t_0 is the number of days from the starting day to the starting day of calculating period of time, θ is the observation day minus initial day divided 100, θ_0 is the starting day of data serial built model minus initial day divided 100, a_0 is constant, a_i, b_{1j}, b_{2j}, c_1,c_2 are regression coefficients.

The process lines of approximation values and errors with the regression model are plotted in Fig. 10.

The forecast ability of above models is shown in Table 1. It is known from Figs. 9 and 10 and Table 1 that the proposed model is feasible and effective. Because of strong learning and universalized capabilities, the process building the models is intelligentized. This method can be very efficiently utilized to remove noise of signals. It is noticeable that the proposed model transcends the regression models in the precision using the approximation for observations.

4.3 Diagnose Characteristics of Dam Crack

A decision table of diagnosing the characteristics of dam crack is built according to the observed data of water level, air temperature, rainfall, uplift pressure and crack

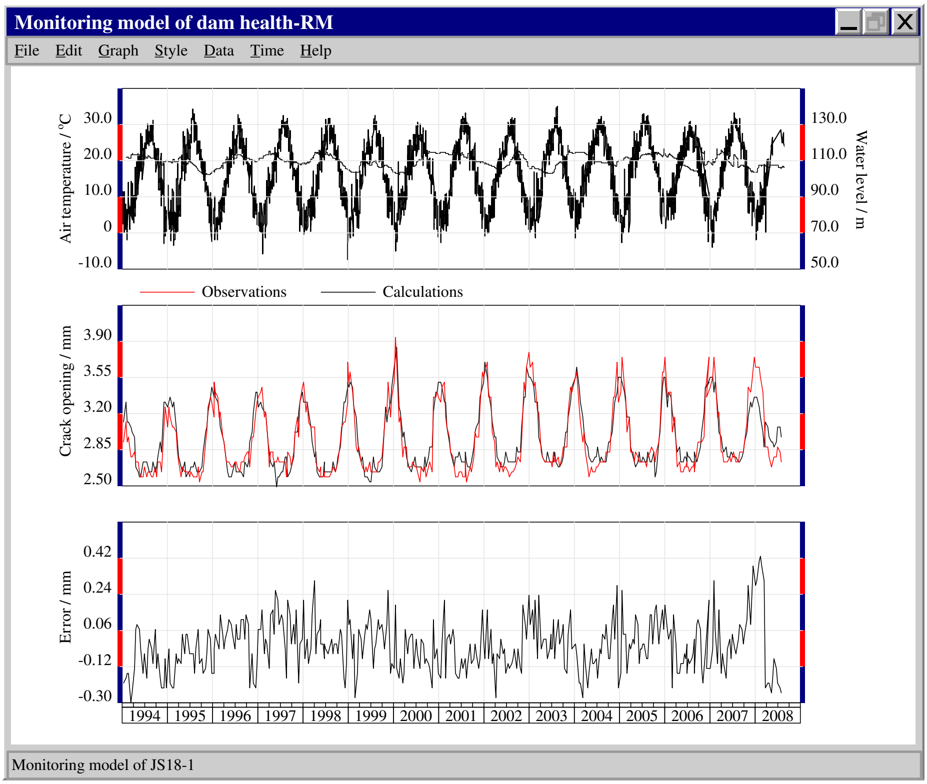


Fig. 10 Process lines of observations, approximations and errors of the regression model

opening of JS18-1 in No. 18 dam section. The upstream water level, down water level, air temperature, rainfall and uplift pressure are regarded as the *condition attribute* (C), $C = \{c_1, c_2, ..., c_5\}$. The crack opening represents the *decision attribute* (D), $D = \{d\}$. The *condition attribute* and *decision attribute* are the continuous variables. A statistical method is used to discriminate the observed data (Lei and Gu 2005). The discriminative partitions are presented in Table 2. The discriminated decision table is presented in Table 3. "1", "2", "3" denotes that water level, temperature, rainfall, uplift pressure and crack opening are high, moderate, low, respectively.

Table 1 Forecast comparison of monitoring models

Assessment index	Regression model	Wavelet network model
Error sum of squares	1.285	0.601
Mean square error	0.062	0.027
Mean absolute error	0.083	0.035

Table 2 Discriminative partitions of the continuous attribute

Discriminated attributes	Attributes					
	c_1 Upstream water level (m)	c_2 Downstream water level (m)	c_3 Temperature (°)	c_4 Rainfall (mm)	c_5 Uplift pressure (m)	d Crack opening (mm)
1	>115	>61	>25	>100	>61	>3.0
2	105–115	59–61	10–25	20–100	59–61	1.5–3.0
3	<105	<59	<10	<20	<59	<1.5

The algorithm proposed in this paper is used to eliminate the redundant attributes for decision table of diagnosing dam cracks (Table 3). Potential geneses of cracks are found with attribute reduction algorithm. Main geneses of cracks are found with attribute least reduction algorithm. "*D-least reduct* of C", namely $mred_D(C)$ is $\{c_1, c_3\}$. It means that the crack opening is mainly affected by the upstream water level and temperature. The fault tree of logical relation between dam cracks and genesis is drawn (See Fig. 11.).

According to the fault tree shown in Fig. 11, the diagnosis rules are extracted. (1) The crack opening is greater than 3 mm when the temperature and water level are low. (2) The crack opening is between 1.5 mm and 3 mm when the temperature is low, and upstream water level is moderate or high. (3) The crack opening is between 1.5 mm and 3 mm when the temperature is moderate. (4) The crack opening is between 1.5 mm and 3 mm when the temperature is high, and upstream water level is moderate or low. (5) The crack opening is less than 1.5 mm when the temperature is high, and upstream water level is high.

The following conclusions can be obtained from above diagnosis rules. The temperature and water level are the significant factors resulting in the emergence and development of dam cracks. The different combinations of water level and temperature have the different influence on crack opening. The combination of low temperature and lower water level can bring the harmful influence on crack opening of JS18-1 in No. 18 dam section.

Table 3 Discriminated decision table

Samples	c_1	c_2	c_3	c_4	c_5	d
s1	3	3	3	3	3	1
s2	3	3	3	2	3	1
s3	2	3	2	3	3	2
s4	3	3	3	3	3	1
s5	2	1	2	3	3	2
s6	2	3	1	2	3	2
s7	2	3	3	3	3	2
s8	2	3	2	3	3	1
s9	2	3	2	2	2	2
s10	3	2	3	3	3	2

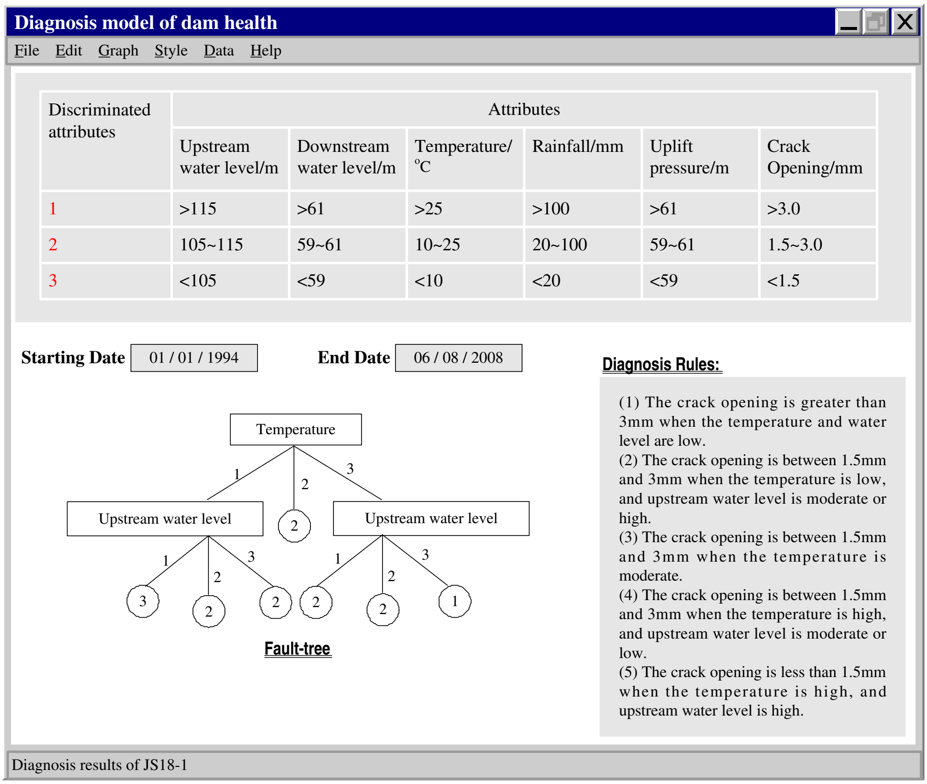


Fig. 11 Sketch map of fault-tree for crack geneses

4.4 Analysis for the Reasonability of the Interference Results

To test above inference results, FEM is used to simulate and analyze the development of crack opening under the typical combinations of temperature and water level.

Fig. 12 The FEM grid

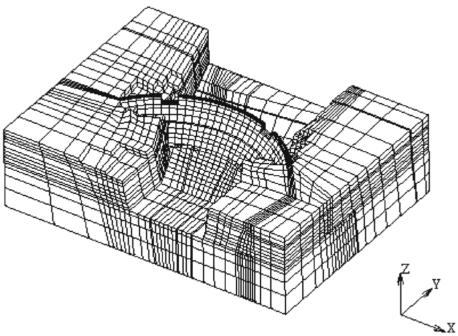


Table 4 Physical and mechanical parameters

Type	Deformation modulus ($\times 10^4$ MPa)	Poisson's ratio	Density (kg/m^3)
Concrete dam body	1.9	0.167	2,400
Rock below El. 70 m at right-bank	1.9	0.2	
Rock below El. 50 m at left-bank	1.3	0.2	
Rock between El. 50 m and El. 86.5 m at two banks	1.0	0.2	
Rock above El. 86.5 m at two banks	0.45	0.2	
Faults (F_{11}, F_{31}, F_{32}, F_{239})	0.05	0.2	

The finite element mesh of the dam's body and foundation is shown in Fig. 12. The number of nodes of finite element mesh is 11,997, and the number of elements is 9,471. The analysis range of the foundation is that the upstream side (from the dam heel to upstream), the downstream side (from the dam heel to downstream) and the level below the base interface are all 2 times higher than the dam. The contact element and the laminar layer element were adopted for joints and weak intercalations, respectively. The main material parameters are shown in Table 4.

In the calculation the 70 groups of load combination condition are considered: higher temperature, middle temperature, lower temperature (−8°C, −6°C, −3°C, 0°C, 5°C, 10°C, 18°C, 25°C, 30°C, 35°C), and higher water level, middle water level, lower water level (90 m, 95 m, 100 m, 105 m, 110 m, 120 m, 126.3 m). The crack opening under different temperature and water level are shown in Fig. 13. To better compare the predicted value, the crack opening under typical combined load conditions are extracted and shown in Table 5. From Fig. 13 and Table 5, it clearly shows that The low temperature and low water level is the worst combination condition for crack stability.

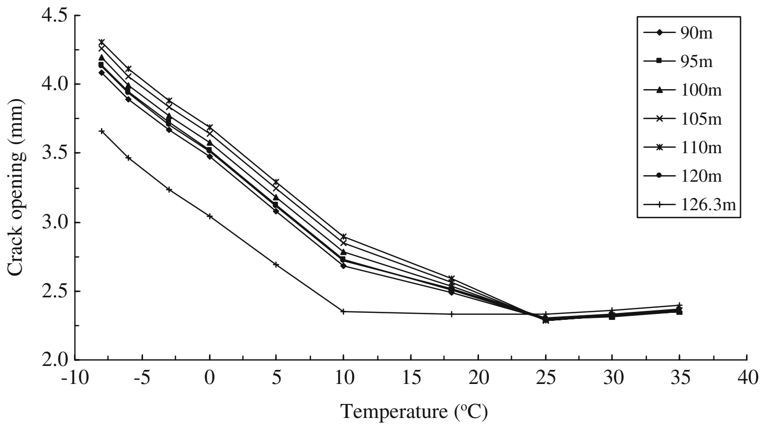


Fig. 13 Developing process of crack

Table 5 The calculated crack opening under load combination conditions

Temperature (°C)	Water level						
	90 m	95 m	100 m	105 m	110 m	120 m	126.3 m
−8	4.083	4.137	4.191	4.261	4.302	4.128	3.657
−6	3.893	3.946	3.997	4.061	4.113	3.939	3.468
−3	3.667	3.721	3.771	3.835	3.883	3.711	3.240
−0	3.472	3.524	3.575	3.640	3.688	3.516	3.047
5	3.076	3.128	3.179	3.244	3.292	3.119	2.696
10	2.680	2.732	2.782	2.847	2.894	2.723	2.346
18	2.485	2.511	2.535	2.567	2.591	2.513	2.335
25	2.295	2.295	2.291	2.289	2.290	2.307	2.329
30	2.325	2.322	2.318	2.319	2.321	2.335	2.358
35	2.349	2.346	2.352	2.358	2.361	2.369	2.395

5 Conclusions

EWSDH is the integration of many theories and methods such as information science, artificial intelligence, material, engineering and management. It translates possibly the off-line, static, passive mode into the on-line, dynamical, active pattern of monitoring dam health.

(1) Dam behavior shows strong non-linear and dynamic characteristics. This system adopts wavelet networks based on wavelet frames to build monitoring models of dam health. According to the observed data, the proposed model describes more reasonably and impersonally operation characteristics of dams. More helpful information can be provided to implement real time and on-line diagnosis of dam health.
(2) Unexpected behaviour diagnosis is the precondition to strength dam. Meanwhile, it is important to manage dam health. In this system, rough sets theory is introduced in the field of diagnosing unexpected behaviour for the first time. With knowledge reduction method of rough sets theory, the system can implement potential geneses mining and main geneses abstracting from decision table. The patterns between unexpected behaviour of dam and geneses can be discovered adaptively with this method.
(3) The applications show that design method is reasonable. The intelligent inference models widen the inference range and improve the inference efficiency of the system. On the other hand, the general design thought and development principle of the system also provides a beneficial reference to monitor slope stability.
(4) Dam health evaluation depends not only on the evaluation for actual observed characteristics of single item and single observation point, but also the whole health state reflected comprehensively by all items and different parts. Evaluation models for dam health will be developed in the future.

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