Structural Monitoring and Maintenance, *Vol. 10, No. 2 (2023) 175-190*
https://doi.org/10.12989/smm.2023.10.2.175

Structural monitoring and maintenance by quantitative forecast model via gray models

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(*Received April 7, 2023, Revised June 2, 2023, Accepted June 5, 2023*)

Abstract. This article aims to quantitatively predict the snowmelt in extreme cold regions, considering a combination of grayscale and neural models. The traditional non-equidistant GM(1,1) prediction model is optimized by adjusting the time-distance weight matrix, optimizing the background value of the differential equation and optimizing the initial value of the model, and using the BP neural network for the first. The adjusted ice forecast model has an accuracy of 0.984 and posterior variance and the average forecast error value is 1.46%. Compared with the GM(1,1) and BP network models, the accuracy of the prediction results has been significantly improved, and the quantitative prediction of the ice sheet is more accurate. The monitoring and maintenance of the structure by quantitative prediction model by gray models was clearly demonstrated in the model.

Keywords: BP network; combined prediction; gray optimization; prediction; structural monitoring and maintenance

1. Introduction

Frost heaving of railway subgrades leads to uneven longitudinal settlement or uplift of rails, which in some cases causes train safety accidents and brings serious safety hazards. Some scholars have conducted related research on the detection of frost heaving of railway subgrades. Wu *et al.* (2022) used the non-contact measurement method of machine vision and optical imaging to realize the real-time monitoring and measurement of the frost heave of the Harbin-Dalian subgrade, and obtained the detection data of the subgrade surface freeze-thaw displacement (hereinafter referred to as the frost heave data). This data reflects the deformation of the railway embankment elevation and has an important impact on the smoothness of the track. At the same time, many scholars at home and abroad have conducted a lot of research on the subgrade frost heave prediction model. Asaoka (2019) proposed the Asaoka method based on the vertical one-way consolidation theory and using the measured subgrade deformation data to calculate the post-construction settlement. Sun (2020) established the GM(1,1) model to predict the subgrade frost heaving data obtained by isochronous sampling of a passenger dedicated line in Northeast my country. Good data has good effect, but it is difficult to predict complex data with many factors. Qi *et al.* (2018) used the inertial correction method in the BP neural network, introduced dynamic learning factors and inertial

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http://www.techno-press.org/?journal=smm&subpage=7 ISSN: 2288-6605 (Print), 2288-6613 (Online)

factors, and established a prediction model for the deformation of the frozen soil subgrade of the Qinghai-Tibet Railway. The disadvantage of this method is that the training process of the neural network model is less stable and has Higher randomness. The prediction model established according to the relevant influencing factors of subgrade frost heave can reflect its development and change, but some of the influencing factors are difficult to quantify, and the prediction accuracy of the model is thus restricted. Most of the subgrade frost heaving prediction methods established at present do not reflect the dynamic randomness and many influencing factors of subgrade frost heaving well, and the prediction effect and accuracy are not ideal. Therefore, this paper adopts the method based on neural network and optimized gray combination model, taking the measurement time series of frost heave data as input, and quantitatively predicts non-equidistant subgrade frost heave data. The advantage of the model in this paper is that the gray model is suitable for small sample prediction and has good stability, but the model is relatively simple and has poor effect on data sources with complex conditions and multiple factors. The model is combined with the neural network to better solve the problem of its application limitation. Based on the input of time series, from the mathematical point of view, the statistical law and potential relationship between frost heave deformation data under the comprehensive action of complex factors can be excavated, so as to achieve the purpose of quantitative prediction with higher precision, and at the same time make the model have better versatility. The significance and value of this research lies in the prediction of frost heave deformation of subgrade, which can assist line maintenance management decision-making, realize early warning of potential safety hazards, and is also of great significance for mastering subgrade frost heave deformation laws.

2. Model building ideas and process

The research object of gray system theory is a small object with known partial information. In order to expand gray The scope of application of color theory, many scholars regard the time interval as the multiplication sub, which is similar to the method of constructing the gray GM(1,1) model to construct A non-equidistant gray GM(1,1) model. The BP network is a Multi-layer forward neural network, which can realize any input to output Non-linear mapping, with strong nonlinear capabilities. general use package The 3 -layer BP network including input layer, hidden layer and output layer can realize Now for any nonlinear signal, the high-precision approximation of the system. therefore, Firstly, the non-equidistant gray GM(1,1) is optimized and improved, and the The optimized non-equidistant gray model is then combined with the BP network, Use the BP network to correct the residual error of the model, learn from each other's strengths, and construct Establish a combined prediction model and apply the model to the frost heaving data of railway subgrade In the prediction of the data, the flow chart of the established model is shown in Figure 1 .

The modeling steps for railway embankment frost heave data include: 1) Carry out a grade test on the original embankment frost heave collection data $x^0 (t_i)$, for different Qualified data carry out translation transformation; 2) Calculate time-distance weighting matrix P according to its time coefficient t(i) of subgrade frost-heave data passing inspection ; 3) Take time distance as multiplier for $x^0 (t_i)$, and accumulate, Obtain the sequence $x^1 (t_i)$; 4) Obtain the constant parameters a and u under the condition of the weighted matrix with the least square method ; 5) Calculate the time response function to obtain the initial predicted value $\delta^0 (t_i)$; 6) Make a difference between the initial predicted value and the original data to get the residual sequence $\Delta d(t_i)$; 7) Input the residual sequence into the BP network model for training, and output the predicted

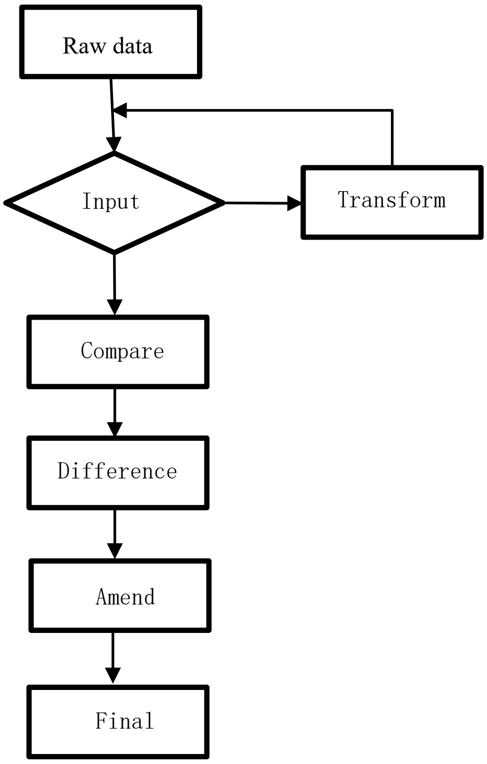

Fig. 1 Modeling block diagram

residual after correction Δ D(t_i) ; 8) Adding the initial predicted value and the predicted residual value to get the final predicted value Q(t_i).

Not all the data can be used for GM(1,1) modeling, only the data satisfying certain conditions, the established GM(1,1) model is meaningful. The Xorder $X = (x_1, x_2, x_3, \dots, x_n)$ratio can be expressed as formula (1). Only at that time , $\phi_k \in (0.1353, 7.389)X$non-deformed GM (1,1) modeling can be done, which is called the basic condition of GM (1,1) modeling .

$$\phi_k = \frac{x_k - 1}{x_k} \tag{1}$$

To establish an effective GM(1,1) model, the practical condition should also be met, that is, the level ratio should fall in a $\varphi_k$subinterval close to 1 $(1-\varepsilon, 1+\varepsilon)$Therefore , this subinterval is called the $(1-\varepsilon, 1+\varepsilon) \in (0.1353, 7.389)$grade boundary area. The method of determining the boundary area of the scale is to Xstart from the boundary area of the original sequence, find out $\varphi_k$the boundary area at last, and then obtain the practical condition of $\varphi_k \in (e^{-\frac{2}{n+1}}, e^{\frac{2}{n+1}})$.

Assuming that $[t_1, t_2, \dots, t_n]$subgrade frost heave sequences are measured within a certain time interval $x^0(t_i)$, a grade comparison test is required before using the original sequence. Level ratio detection is to check whether the original data sequence calculated by formula (1) $\varphi(i)$falls within the limited interval $(e^{-\frac{2}{n+1}}, e^{\frac{2}{n+1}})$, if it falls within the interval, the data can be used directly, otherwise translation transformation is required, as shown in formula (2), select an appropriate The constant c, until the calculated $\varphi'(i)$new sequence $x'^0(t_i)$falls within the limited interval, at this time, the new sequence can be predicted and analyzed, and the predicted analysis is completed, and then the inverse transformation is restored.

$$x'^0(t_i) = x^0(t_i) + c \ , \quad \text{in} i = 1,2,3,\dots,n \tag{2}$$

Calculate the time interval series $\Delta t(k)$according to the time series $t(i)$, where $k = 2, 3, \dots, n$. The time interval is used as the multiplier, and $x^0(t_i)$the sequence is accumulated once, as shown in formula (3), to obtain the sequence $x^1(t_i)$. The differential equation of whitening form can be established from the sequence $x^1(t_i)$, such as formula (4), where it $\alpha$is called the development coefficient and $u$the gray action. The role of the two is to control the uncertainty relationship between the size of the development situation of the gray system and the change of the response data.

$$x^1(t_i) = \sum_{k=2}^{1} x^0(t_k)\Delta t_k \ \ , i = 1,2,3,\dots,n \tag{3}$$

$$\frac{dx^1(t)}{dt} + ax'(t) = v \ \ , t \in [0, \infty) \tag{4}$$

Integrate the formula (4) in $[t_{i-1}, t_i]$the interval to get the formulas (5) and (6), and the formula $z^1(t_i)$is the background value on $x^1(t_i)$the interval $[t_{i-1}, t_i]$. In order to obtain $a$and u 2 parameter values, use the least square method to formula (3) to get formula (7) and (8) 2 formula

$$x^0(t_i)\Delta t^i + az^1(t_i) = v\Delta t_i \ \ , i = 2,3,\dots,n \tag{5}$$

$$z^1(t_i) = \int_{t_{i-1}}^{t_i} x1(t)dt = \frac{1}{2}(x^1(t_{i-1}) + x^1(t_i)) \tag{6}$$

$$(\alpha, v)^T = (B^T B)^{-1} B^T Y \tag{7}$$

$$B = \begin{bmatrix} -z^1(t_2) & \Delta t_2 \\ \vdots & \vdots \\ -z^1(t_n) & \Delta t_n \end{bmatrix}, \quad Y = \begin{bmatrix} x^0(t_2)\Delta t_2 \\ \vdots \\ x^0(t_n)\Delta t_n \end{bmatrix} \tag{8}$$

If the initial value is specified $x^1(t_i) = x^0(t_i)$, then the time response function of formula (4) can be obtained as formula (9). Restore $x^0(t_i)$the non-isochronous GM(1,1) model sequence that fits the original sequence $\delta^0(t_i)$as formula (10)

$$\delta^1(t_i) = \left[-x^0(t_i) - \frac{v}{\alpha}\right] e^{-\alpha(t_i - t_1)} \tag{9}$$

$$\delta^0(t_i) = \frac{\delta^1(t_i) - \delta^1(t_{i-1})}{\Delta t_i} = \frac{(1 - e^{\alpha \Delta t_i})}{\Delta t_i} \left[x^0(t_1) - \frac{v}{\alpha}\right] e^{-\alpha(t_i - t_1)} \tag{10}$$

obtaining the initial prediction sequence $\delta^0(t_i)$, use the MATLAB neural network toolkit t o establish a BP network model and correct the residual.

Since the 3-layer BP network can approximate any nonlinear signal and system with arbitrary precision, considering the computational efficiency, a 3-layer BP network with a hidden layer is established. The input layer input is the residual sequence obtained by comparing the initial prediction of the optimized gray prediction model with the original data $\Delta d(t_i)$. The number of neurons in the hidden layer of the network is generally selected according to formula (11), where

$p$and is $q$the number of neurons in the input and output layers, and α is a constant between (0,10)

$$n = \sqrt{p+q} + a \tag{11}$$

The larger the number of neurons, the higher the training accuracy, but the slower the training rate, and it is prone to overfitting. The smaller the number of neurons, the faster the training speed, but it may lead to poor learning effect. Therefore, the model α in this paper is set to 9, and the number of neurons calculated by formula (11) is 10. The transfer function between the input layer and the hidden layer is selected as the tangsig hyperbolic tangent S-type transfer function, and the transfer function between the hidden layer and the output layer is a purelin linear transfer function. The output layer is the residual value of the network fit. The self-adaptive variable step size BP algorithm is selected, the learning results are observed, the network training parameters are continuously adjusted, the network is trained, and the post-training residual correction sequence is obtained $\Delta D(t_i)$. Predicted value of final subgrade frost heave $Q(t_i)$.

After adjusting the parameters several times and observing the test results, the optimal learning parameter settings determined in this paper are: learning rate 0.05, model training error precision 0.000 5, and training times 1000 times.

In the non-equidistant GM(1,1) model mentioned above, the background value is calculated by using the trapezoidal formula to approximate the $x^1(t_i)$area enclosed by the cumulative sequence and the x- axis on the interval . $[t_{i-1}, t_i]$But when the accumulated sequence changes drastically within this interval, the background value calculated by formula (6) has a large error. Literature [7] proposes a background value calculation method based on integral reconstruction, and proves that the background value constructed by this method is more in line with the actual conditions. In this method, the exponential function cert is used to approximate the cumulative sequence $x^1(t_i)$, where the sum $c$and $r$are both undetermined coefficients, which are substituted into formula (6) to obtain the optimized background value calculation as formula (12)

$$z^1(t_i) = \frac{[x^1(t_i) - x^1(t_i - 1)]\Delta t_i}{\ln x^1(t_i) - \ln x^1(t_{i-1})} \tag{12}$$

In the data sequence used to establish the non-equidistant GM(1,1) model, each data has different effects on the model. For the existing data, it can be considered that the detection accuracy is the same, so it can be considered that the closer the data is to the prediction time point, the greater the role it plays in the prediction model and the higher the reliability. Each item of the original data sequence is given a weight value, and the size of the weight value is related to the time interval between the item data and the predicted data. Therefore, this paper proposes a weighted matrix based on the time interval

Define the increment factor $W$and growth rate $w(j)$, and $w(1) = 1$, $w(2) = 2$, where the increment factor $W$is a constant between (1,2). The value of the increment factor Wcan depend on time

The correlation of factors in the model, the larger the value, the more important the time factor. The growth rate $w(j)$represents the time interval factor, and the smaller the interval between the data and the forecast time point, the higher the reliability in the forecast model, and the greater the weight value. Therefore, the formula for defining the weighting matrix $\boldsymbol{P}$ is as formula (12)

$$P = \begin{bmatrix} W^{w(1)} & 0 & 0 & 0 \\ 0 & W^{w(2)} & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & W^{w(n)} \end{bmatrix},$$

$$w(j)=\frac{t(j)-t(2)}{t(2)-t(1)}+1\ ,j=3,4,\dots,n \tag{12}$$

After defining the weight matrix, the least square method is used to calculate the development system, $a$and $u$the formula (7) with the gray action is changed to the formula (13)

$$(\alpha,v)^T=(B^TPB)^{-1}B^TPY \tag{13}$$

In the non-equidistant GM(1,1) model, Initial value optimization based on the minimum cumulative residual error is defined $x^1(t_1)=x^0(t_1)$, and the first value of the original data sequence is used as the initial value. However, in the actual embankment frost heave data fitting, the best fitting curve does not necessarily pass through a certain point on the original data, and the initial value in [7] is simply the mean value of the measured data. These initial value selection methods lack theoretical basis and will reduce the accuracy of the model. Therefore, this paper uses the method of calculating the minimum cumulative residual to determine the initial value. Define the initial value $x^1(t_1)=x^0(t_1)+b$, $b$that is, optimize the parameters for the initial value. Therefore, the final prediction formula (10) is changed to

$$\sigma^0=\frac{(1-e\alpha^{\Delta t_i})}{\Delta t_i}\left[x^0(t_1)+b-\frac{v}{\alpha}\right]e^{-\alpha(t_i-t_1)} \tag{14}$$

The formula for calculating the cumulative residual *E* is written as

$$E=\sum_{i=2}^{n}[x^0(t_i)-\delta^0(t_i)]^2+b^2 \tag{15}$$

To make E the smallest, calculate the partial derivative expression of formula (15) with respect to b, and set its value to 0 , and the value formula (16) of b under the condition of minimum cumulative residual error can be obtained

$$b=\frac{\sum_{i=2}^{n}\frac{1}{\Delta t_i}(1-e^{\alpha\Delta t_i})e^{-\alpha t_i}x^0(t_i)+\sum_{i=2}^{n}[\frac{1}{\Delta t_i}(1-e^{\alpha\Delta t_i})e^{-\alpha t_i}]^2[x^0(t_1)-\frac{v}{\alpha}]}{1+[\frac{1}{\Delta t_i}(1-e^{\alpha\Delta t_i})e^{-\alpha t_i}]^2} \tag{16}$$

3. A numerical example

In 2012-12, the Harbin-Dalian Passenger Dedicated Line was officially opened for operation. The average monthly temperature in winter along the line was -13.5~-17.5°C, the extreme low temperature reached -40°C, the maximum freezing depth of the soil reached 205 cm, and frost heave was common throughout the subgrade. The data from 2013-12-19 to 2014-01-26 at k 186+600 in the downlink of Bayuquan on the Harbin-Dalian Passenger Dedicated Line is selected as the prediction test value to test the prediction effect of the model in this paper. The actual measurement data are shown in Table 1. Table 1 The measured values are all the freeze-thaw displacement values of the roadbed surface.

According to the modeling method mentioned above, the data is firstly tested for grades. The number of data $n=19$ can be calculated to obtain a limited interval of $(0.905,1.105)$. The original data calculated by formula (1) $\varphi_{max}=1.268$exceeds the limited interval, so the original data is translated and changed, and the translation constant c in formula (2) is set to 5, that is, the calculated $x'^0(t_i)=x^0(t_i)+5$data sequence after transformation can be obtained $\varphi_{max}=1.072$, $\varphi_{min}=1.009$, passed the grade ratio test. Therefore, according to the modeling steps

Table 1 Actual measurement data

measurement date	Measured value/ mm	measurement date	Measured value/ mm	measurement date	Measured value/ mm
2 013-12-19	1.83 _	2 013-12-27	4.30 _	2 014-01-14	5.78 _
2 013-12-20	2.32 _	2 013-12-29	4.46	2014-01-18	6.18
2013-12-21	2.56	2014-01-03	4.67	2014-01-19	6.78
2013-12-22	2.96	2014-01-08	4.97	2014-01-22	6.98
2013-12-23	3.23	2014-01-09	5.11	2014-01-26	7.28
2013-12-24	3.63	2014-01-12	5.23		
2013-12-25	4.17	2014-01-13	5.68		

Table 2 Fitting effect comparison

measurement date	time factor	Measurements	BP network model		G M(1,1) model		This paper model	
			fitted value	Relative error%	fitted value	Relative error%	fitted value	Relative error%
2 December 19, 2013	0	1.83 _	1.8461 _	0.88 _	1.8300 _	0	1.8185 _	0.6284
2013/12/20	1	2.32	2.2853	1.50	2.6471	14.1	2.5128	8.3100
2013/12/21	2	2.56	2.6820	4.77	2.7403	7.04	2.7010	5.5078
2013/12/22	3	2.96	2.9382	0.74	2.8345	4.24	2.8020	5.3378
2013/12/23	4	3.23	3.1185	3.45	322953	2.02	3.1411	2.7500
2013/12/24	5	3.63	3.6037	0.72	3.3255	8.39	3.6669	1.0165
2013/12/25	6	4.17	4.2666	2.32	3.7224	10.73	4.1517	0.4388
2013/12/27	8	4.30	4.4246	2.90	3.9196	8.85	4.3062	0.1442
2013/12/29	10	4.46	4.4387	0.48	4.1961	5.92	4.4603	0.0067
2013/01/03	14	4.67	4.4942	3.76	4.3761	6.29	4.6710	0.0214
2013/01/08	19	4.97	4.9553	0.30	5.2531	5.70	4.9339	0.7264
2013/01/09	20	5.11	5.1206	0.21	5.5815	9.23	5.1455	0.6947
2013/01/12	23	5.23	5.4829	4.84	5.8068	11.03	5.2460	0.3059
2013/01/13	24	5.68	5.5974	1.45	6.0358	6.26	5.6444	0.6268
2013/01/14	25	5.78	5.7124	1.17	6.1521	6.44	5.8398	1.0346
2013/01/18	29	6.18	6.1075	1.17	6.4486	4.35	6.1456	0.5566

introduced above, firstly use the $x'^0(t_i)$ first 16 items of the shifted data to establish an optimization model, define the weight increment factor in the model $W = 1.4$, and obtain the initial predicted value. The initial gray model prediction error is shown in Fig. 2. It can be seen from Fig. 2 that the initial residual has a high degree of nonlinearity. Then bring the initial prediction value and the residual calculated by the original data into the BP network for training, take the number of neurons in the hidden layer as 8, and obtain the residual sequence after training, add the residual sequence to the initial prediction value, The fitting sequence of the optimized model can be obtained, and finally the translation inverse transformation is performed to obtain the final prediction result, which is compared with the actual frost heave data as shown in Fig. 3.

Table 2 shows the results of comparing the measured values of the optimized model fitting with the fitting measured values of the GM (1,1) model in literature [3] and the BP neural network

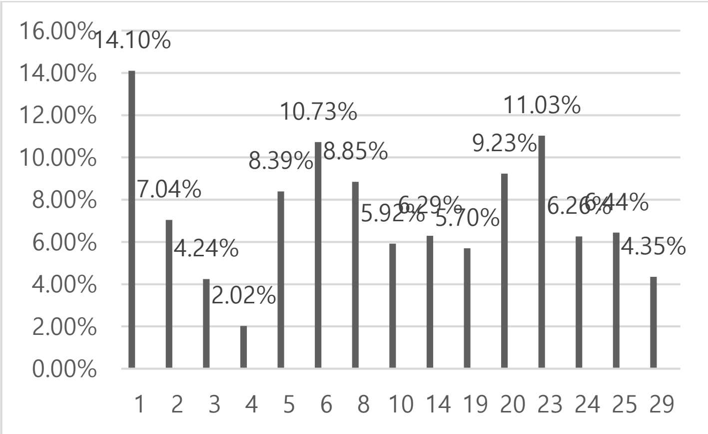

Fig. 2 Gray model fitting error plot

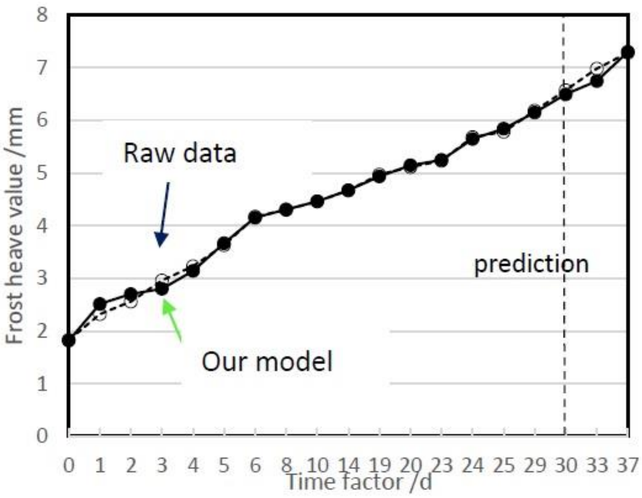

Fig. 3 Comparison between prediction model data and actual measurement data

model in literature [4]. Afterwards, the remaining three time coefficients were input to the three models respectively to obtain three sets of forecast sequences, and the comparison results with the original data are shown in Table 3.

In order to verify the optimization effect of the time-distance weighted matrix optimization item proposed in this paper and the optimization item based on the minimum residual initial value, the combination model that lacks the time-distance weighted matrix optimization item proposed above and retains the remaining optimization items is defined as model A. Define The combination model that lacks the initial value optimization item proposed above and retains the rest of the optimization items is model B. Compared with the complete optimization combination model in this paper, the prediction results are shown in Table 4.

Table 3 Comparison of prediction effects (1)

measurement date	time factor	Measurements	BP network model		G M(1,1) model		This paper model	
			fitted value	Relative error%	fitted value	Relative error%	fitted value	Relative error%
2 January 19, 2014	3 0	6.57 _	6.1782 _	6.34 _	6.7508	2.75	6.4918	1.1903
2014/01/22	33	6.98	6.3225	10.4	7.3989	6	6.7446	2.9427
2014/01/26	37	7.28	6.4076	13.62	7.9443	9.12	7.2989 _	0.2596 _

Table 4 Comparison of prediction effects (2)

measurement date	time factor	Measurements	Model A		Model B		This paper model	
			fitted value	Relative error%	fitted value	Relative error%	fitted value	Relative error%
2 January 19, 2014	3 0	6.57 _	6.4762 _	1.4277 _	6.4324 _	2.0440 _	6.4918 _	1.1903 _
2014/01/22 _	3 3	6.98 _	6 .7403	3.4341 _	6.7136 _	3.8166	6.7446	2.9427
2014/01/26	37	7.28	7.1858	1.2940	7.2353	0.6140	7.2989	0.2596

By observing the above charts, it can be concluded that the combined prediction model of non-equidistant gray optimization and neural network established in this paper has an average prediction error of 1.46%. It can be seen from Figure 1 that the combined prediction model has achieved more accurate fitting and forecasting. However, the GM(1,1) model method established in literature [3] has an average prediction error of 5.69%, and the BP neural network model method established in literature [4] has an average prediction error of 10.12%, both of which are much higher than the model in this paper. It can be concluded that the prediction accuracy of the subgrade frost heave combination prediction model proposed in this paper is significantly improved compared with the existing methods. However, the average prediction errors of model A and model B are 2.052% and 2.1582%, respectively, and the accuracy is slightly lower than that of the model in this paper. optimization effect.

At the same time, in order to verify the reliability and accuracy of the optimized combination prediction model in this paper for the prediction of frost heave of railway subgrade, the posterior difference ratio in statistics is used to Cverify the accuracy of the model $.p$

Relative residuals

$$\mu(t_i) = \frac{\delta^1(t_i) - x^0(t_i)}{x^0(t_i)} \times 100\% \tag{17}$$

Average Residuals

$$\mu' = \frac{1}{n-1} \sum_{i=2}^{n} |\mu(t_i)| \tag{18}$$

Residual variance

$$S_1 = \frac{1}{n} \sum_{i=1}^{n} (\mu(t_i) - \mu')^2 \tag{19}$$

Assuming the variance of the original data S_2, the posterior difference ratio is expressed as

$$C = \sqrt{S_1 / S_2} \tag{20}$$

Modeling accuracy

$$p = (1 - \mu') \times 100\% \tag{21}$$

The model in this paper is obtained by calculation $p = 98.4\%$. The larger the model accuracy value, p the higher the model accuracy, and the smaller the posterior difference ratio C, the smaller the dispersion of the prediction error. Referring to the model accuracy test table [8], it can be concluded that the prediction accuracy and reliability of this model for frost heave of railway embankment are high, and the accuracy level reaches level 1.

4. Conclusions

1) The background value and initial value of the differential equation of the non-equidistant GM(1,1) model were optimized by integral reconstruction and the method based on the minimum cumulative residual error, which improved the prediction accuracy of the model.

2) Set the weight matrix for the non-equidistant GM(1,1) model, fully consider the development trend of subgrade frost heave deformation, and improve the reliability of the prediction results.

3) Use the BP neural network residual correction model to correct the initial prediction data of the optimized non-equidistant GM (1,1) model, which makes up for the shortcomings of the gray prediction model in nonlinear prediction, improves the prediction accuracy of the model, and broadens the horizon. range of use of the model.

References

Bedirhanoglu, I. (2014), "A practical neuro-fuzzy model for estimating modulus of elasticity of concrete", *Struct. Eng. Mech*., **51**(2), 249-265. https://doi.org/10.12989/sem.2014.51.2.249.

Chen, C. (2002), "A neural-network approach to modeling and analysis", *Proceedings of the International Conference on Tools with Artificial Intelligence*, 489-493.

Chen, C. (2002), "A stability criterion of time-delay fuzzy systems", *J. Mar. Sci. Technol*., **10**(1), 33-35.

Chen, C. (2003), "Flow characteristics inside large porous structure by constant head device", *Chung Cheng Ling Hsueh Pao/J. Chung Cheng Inst. Technol.*, **32**(1), 1-15.

Chen, C. (2004), "A study of PDC fuzzy control of structural systems using LMI approach", *Proceedings of the IASTED International Conference. Applied Informatics*.

Chen, C. (2004), "Fuzzy regression to construction management via T-S fuzzy model", *Proceedings of the IASTED International Conference. Applied Informatics*.

Chen, C. (2005), "Fuzzy logic derivation of neural network models with time delays in subsystems", *Int. J. Artif. Intell. Tools*, **14**(6), 967-974. https://doi.org/10.1142/S021821300500248X.

Chen, C. (2006), "A novel fuzzy regression approach on managing target cash balance for construction firms", *Proceedings of the IASTED International Conference on Modelling and Simulation*.

Chen, C. (2006), "Fuzzy lyapunov method for stability conditions of nonlinear systems", *Int. J. Artif. Intell. Tools*, **15**(2), 163-171. https://doi.org/10.1142/S0218213006002618.

Chen, C. (2006), "Numerical model of internal solitary wave evolution on impermeable variable seabed in a stratified two-layer fluid system", *China Ocean Eng*., **20**(2), 303-313.

Chen, C. (2006), "Stability conditions of fuzzy systems and its application to structural and mechanical

systems", *Adv. Eng. Softw.*, **37**(9), 624-629. https://doi.org/10.1016/j.advengsoft.2005.12.002.
Chen, C. (2007), "A novel delay-dependent criterion for time-delay T-S fuzzy systems using fuzzy lyapunov method", *Int. J. Artif. Intell. Tools*, **16**(3), 545-552. https://doi.org/10.1142/S0218213007003400.
Chen, C. (2007), "An experimental study of stratified mixing caused by internal solitary waves in a two-layered fluid system over variable seabed topography", *Ocean Eng.*, **34**(14-15), 1995-2008. https://doi.org/10.1016/j.oceaneng.2007.02.014.
Chen, C. (2007), "Generation of internal solitary wave by gravity collapse", *J. Mar. Sci. Technol.*, **15**(1), 1-7.
Chen, C. (2007), "Interfacial wave motion in an impermeable rigid channel with stratified density fluid system, 2, waveform feature against stratification thickness ratio", *Shuikexue Jinzhan/Advances in Water Science*, **18**(4), 575-579.
Chen, C. (2007), "Laboratory observations on internal solitary wave evolution on steep and inverse uniform slopes", *Ocean Eng.*, **34**(1), 157-170. https://doi.org/10.1016/j.oceaneng.2005.11.019.
Chen, C. (2007), "Modeling, H∞ control and stability analysis for structural systems using takagi-sugeno fuzzy model", *J. Vib. Control*, **13**(11), 1519-1534. https://doi.org/10.1177/1077546307073690.
Chen, C. (2007), *Stability analysis for floating structures using T-S fuzzy control*, https://doi.org/10.1007/978-3-540-74205-0_79.
Chen, C. (2009), "A stability criterion for time-delay tension leg platform systems subjected to external force", *China Ocean Eng.*, **23**(1), 49-57.
Chen, C. (2009), "Adaptive fuzzy sliding mode control for seismically excited bridges with lead rubber bearing isolation", *Int. J. Uncertainty, Fuzziness and Knowldege-Based Syst.*, **17**(5), 705-727. https://doi.org/10.1142/S0218488509006224.
Chen, C. (2009), "Managing target the cash balance in construction firms using a fuzzy regression approach", *Int. J. Uncertainty, Fuzziness Knowldege-Based Syst.*, **17**(5), 667-684. https://doi.org/10.1142/S0218488509006200.
Chen, C. (2009), "Modeling and control for nonlinear structural systems via a NN-based approach", *Exp. Syst. Appl.*, **36**(3), 4765-4772. https://doi.org/10.1016/j.eswa.2008.06.062.
Chen, C. (2009), "The stability of an oceanic structure with T-S fuzzy models", *Math. Comput. Simul.*, **80**(2), 402-426. https://doi.org/10.1016/j.matcom.2009.08.001.
Chen, C. (2010), "Application of fuzzy-model-based control to nonlinear structural systems with time delay: An LMI method", *J. Vib. Control*, **16**(11), 1651-1672. https://doi.org/10.1177/1077546309104185.
Chen, C. (2010), "Applying half-circle fuzzy numbers to control system: A preliminary study on development of intelligent system on marine environment and engineering", World Academy of Science, Engineering and Technology, **72**, 71-75.
Chen, C. (2010), "Fuzzy control for an oceanic structure: A case study in time-delay TLP system", *J. Vib. Control*, **16**(1), 147-160. https://doi.org/10.1177/1077546309339424.
Chen, C. (2010), "Linking the balanced scorecard (BSC) to business management performance: A preliminary concept of fit theory for navigation science and management", *Int. J. Phys. Sci.*, **5**(8), 1296-1305.
Chen, C. (2010), "Modeling and fuzzy PDC control and its application to an oscillatory TLP structure", *Math. Probl. Eng.*, https://doi.org/10.1155/2010/120403.
Chen, C. (2010), "Stability analysis of an oceanic structure using the lyapunov method", *Eng. Comput.*, **27**(2), 186-204. https://doi.org/10.1108/02644401011022364.
Chen, C. (2010), "Stability analysis of interconnected fuzzy systems using the fuzzy lyapunov method", *Math. Probl. Eng.*, https://doi.org/10.1155/2010/734340.
Chen, C. (2010), "The study of a forecasting sales model for fresh food", *Exp. Syst. Appl.*, **37**(12), 7696-7702. https://doi.org/10.1016/j.eswa.2010.04.072.
Chen, C. (2011), "A critical review of nonlinear fuzzy multiple time-delay interconnected systems using the lyapunov criterion", *Scientific Res. Essays*, **6**(28), 5917-5932. https://doi.org/10.5897/SRE11.1347.
Chen, C. (2011), "Modeling, control, and stability analysis for time-delay TLP systems using the fuzzy lyapunov method", *Neural Comput. Appl.*, **20**(4), 527-534. https://doi.org/10.1007/s00521-011-0576-8.
Chen, C. (2011), "Stability analysis and robustness design of nonlinear systems: An NN-based approach",

Appl. Soft Comput. J., **11**(2), 2735-2742. https://doi.org/10.1016/j.asoc.2010.11.004.
Chen, C. (2012), “A novel strategy to determine the insurance and risk control plan for natural disaster risk management”, *Nat. Hazards*, **64**(2), 1391-1403. https://doi.org/10.1007/s11069-012-0305-3.
Chen, C. (2012), “Disaster prevention and reduction for exploring teachers' technology acceptance using a virtual reality system and partial least squares techniques”, *Nat. Hazards*, **62**(3), 1217-1231. https://doi.org/10.1007/s11069-012-0146-0.
Chen, C. (2012), “Human factors of knowledge-sharing intention among taiwanese enterprises: A model of hypotheses”, *Human Factors Ergonomics in Manufact.*, **22**(4), 362-371. https://doi.org/10.1002/hfm.20286.
Chen, C. (2013), “Topology-aware handoff scheme for surveillance patrol robot”, *Nonlinear Dynam.*, **73**(3), 2073-2081. https://doi.org/10.1007/s11071-013-0923-7.
Chen, C. (2014), “A criterion of robustness intelligent nonlinear control for multiple time-delay systems based on fuzzy lyapunov methods”, *Nonlinear Dynam.*, **76**(1), 23-31. https://doi.org/10.1007/s11071-013-0869-9.
Chen, C. (2014), “Interconnected TS fuzzy technique for nonlinear time-delay structural systems”, *Nonlinear Dynam.*, **76**(1), 13-22. https://doi.org/10.1007/s11071-013-0841-8.
Chen, C.W. and Chen, P.C. (2010), “Ga-based adaptive neural network controllers for nonlinear systems”, *Int. J. Innov. Comput. Inform. Control*, **6**(4), 1793-1803.
Chen, C.W. (2004), “Stability analysis of T-S fuzzy models for nonlinear multiple time-delay interconnected systems”, *Math. Comput. Simul.*, **66**(6), 523-537. https://doi.org/10.1016/j.matcom.2004.04.001.
Chen, C.W. (2006), “Application of modeling and control to structural systems”, *Proceedings of the IASTED International Conference on Modelling and Simulation*, 226-227.
Chen, C.W. (2007), “Application of fuzzy stability control for buildings”, *Proceedings of the IASTED International Conference on Artificial Intelligence and Applications*, AIA 2007, 551-553.
Chen, C.W., Chen, P.C. and Chiang, W.L. (2011), “Stabilization of adaptive neural network controllers for nonlinear structural systems using a singular perturbation approach”, *J. Vib. Control*, **17**(8), 1241-1252. https://doi.org/10.1177/1077546309352827.
Chen, C.Y.J., (2020), “System simulation and synchronization for optimal evolutionary design of nonlinear controlled systems”, *Smart Struct. Syst.*, **26**(6), 797-807. https://doi.org/10.12989/sss.2020.26.6.797.
Chen, C.Y. (2007), “An investigation on internal solitary waves in a two-layer fluid: Propagation and reflection from steep slopes”, *Ocean Eng.*, **34**(1), 171-184. https://doi.org/10.1016/j.oceaneng.2005.11.020.
Chen, G. (2008), “Stability analysis for time delay TLP systems”, *Proceedings of the IEEE/ASME International Conference on Advanced Intelligent Mechatronics*, AIM. https://doi.org/10.1109/AIM.2008.4601816.
Chen, P. (2009), “A novel stability condition and its application to GA-based fuzzy control for nonlinear systems with uncertainty”, *J. Mar. Sci. Technol.*, **17**(4), 293-299.
Chen, P. (2009), “Stability analysis of fuzzy control for nonlinear systems”, *Proceedings of the 2009 1st Asian Conference on Intelligent Information and Database Systems*, ACIIDS. https://doi.org/10.1109/ACIIDS.2009.83.
Chen, P. (2011), “Linear matrix inequality conditions of nonlinear systems by genetic algorithm-based H ∞ adaptive fuzzy sliding mode controller”, *J. Vib. Control*, **17**(2), 163-173. https://doi.org/10.1177/1077546309352826.
Chen, P.C. (2011), “GA-based decoupled adaptive FSMC for nonlinear systems by a singular perturbation scheme”, *Exp. Syst. Appl.*, **3620**(4), 517-526.
Chen, P.C. (2008), “GA-based fuzzy sliding mode controller for nonlinear systems”, *Math. Probl. Eng.*, https://doi.org/10.1155/2008/325859.
Chen, P. C. (2009), “GA-based modified adaptive fuzzy sliding mode controller for nonlinear systems”, *Exp. Syst. Appl.*, **36**(3), 5872-5879. https://doi.org/10.1016/j.eswa.2008.07.003.
Chen, T. (2008), “A mathematical tool for inference in logistic regression with small-sized data sets: A practical application on ISW-ridge relationships”, *Math. Probl. Eng.*, https://doi.org/10.1155/2008/186372.

Chen, T. (2010), “Application of data mining to the spatial heterogeneity of foreclosed mortgages”, *Exp. Syst. Appl*., **37**(2), 993-997. https://doi.org/10.1016/j.eswa.2009.05.076.
Chen, T. (2019), “An empirical study among science education majors in postgraduate students of an australian university”, *Comput. Appl. Eng. Educ.*, **27**(4), 986-993. https://doi.org/10.1002/cae.8.
Chen, T. (2019), “An empirical study of computer science majors’ intentions in vietnamese higher education”, *Comput. Appl. Eng. Educ*., **27**(4), 814-820. https://doi.org/10.1002/cae.22090.
Chen, T. (2019), “Hazard data analysis for underwater vehicles by submarine casualties”, *Mar. Technol. Soc. J*., **53**(6), 21-26. https://doi.org/10.4031/MTSJ.53.6.2
Chen, T. (2019), “Meteorological tidal predictions in the mekong estuary using an evolved ANN time series”, *Mar. Technol. Soc. J.*, **53**(6), 27-34. https://doi.org/10.4031/MTSJ.53.6.3.
Chen, T. (2019), “Modelling and verification of an automatic controller for a water treatment mixing tank”, *Desalination and Water Treatment*, **159**, 318-326. https://doi.org/10.5004/dwt.2019.24143.
Chen, T. (2020), “Decentralized fuzzy C-means robust algorithm for continuous systems”, *Aircraft Eng. Aerosp. Technol*., **92**(2), 222-228. https://doi.org/10.1108/AEAT-04-2019-0082.
Chen, T. (2020), “Hierarchical intelligence platform designed for wastewater management systems: Information technology integration”, *Desalination and Water Treatment*, **183**, 167-172. https://doi.org/10.5004/dwt.2020.25179.
Chen, T. (2020), “Intelligent fuzzy algorithm for nonlinear discrete-time systems”, *T. Inst. Measurement Control*, **42**(7), 1358-1374. https://doi.org/10.1177/0142331219891383.
Chen, T. (2020), “Using evolving ANN-based algorithm models for accurate meteorological forecasting applications in Vietnam”, *Math. Probl. Eng*., https://doi.org/10.1155/2020/8179652.
Chen, T. (2021), “Evolved auxiliary controller with applications to aerospace”, *Aircraft Eng. Aerosp. Technol*., **93**(4), 529-543. https://doi.org/10.1108/AEAT-12-2019-0233.
Chen, T. (2021), “Evolved predictive vibration control for offshore platforms based on the lyapunov stability criterion”, *Ships Offshore Struct*., **16**(7), 700-713. https://doi.org/10.1080/17445302.2020.1776548.
Chen, T. (2021), “Smart structural stability and NN based intelligent control for nonlinear systems”, *Smart Struct. Syst.*, **27**(6), 917-923. https://doi.org/10.12989/sss.2021.27.6.917.
Chen, T., Dkuo, N.J. and Chen, C.Y.J. (2020), “A composite control for UAV systems with time delays”, *Aircraft Eng. Aerosp. Technol*., **92**(7), 949-954. https://doi.org/10.1108/AEAT-11-2019-0219.
Chen, T., Lohnash, M., Owens, E. and Chen, C.Y.J. (2020), “PDC intelligent control-based theory for structure system dynamics”, *Smart Struct. Syst*., **25**(4), 401-408. https://doi.org/10.12989/sss.2020.25.4.401.
Chen, Z. (2002), “Fuzzy control for nonlinear systems modeled via neural-network”, *Proceedings of the IEEE International Conference on Industrial Technology*. https://doi.org/10.1109/ICIT.2002.1189863.
Chen, Z.Y. (2021), “Grey signal predictor and evolved control for practical nonlinear mechanical systems”, *J. Grey Syst*., **33**(1), 156-170.
Chen, Z.Y., (2021), “Active TMD systematic design of fuzzy control and the application in high-rise buildings”, *Earthq. Struct*., **21**(6), 577-585. https://doi.org/10.12989/eas.2021.21.6.577.
Chen, Z.Y. (2021), “Apply a robust fuzzy LMI control scheme with AI algorithm to civil frame building dynamic analysis”, *Comput. Concrete*, **28**(4), 433-440. https://doi.org/10.12989/cac.2021.28.4.433.
Chen, Z.Y. (2022), “Bridges dynamic analysis under earthquakes using a smart algorithm”, *Earthq. Struct*., **23**(4), 329-338. https://doi.org/10.12989/eas.2022.23.4.329.
Chen, Z.Y. (2022), “Composite components damage tracking and dynamic structural behaviour with AI algorithm”, *Steel Compos. Struct*., **42**(2), 151-159. https://doi.org/10.12989/scs.2022.42.2.151.
Chen, Z.Y. (2022), “Fuzzy neural network controller of interconnected method for civil structures”, *Adv. Concrete Constr*., **13**(5), 385-394. https://doi.org/10.12989/acc.2022.13.5.385.
Chen, Z.Y. (2022), “LQG modeling and GA control of structures subjected to earthquakes”, *Earthq. Struct*., **22**(4), 421-430. https://doi.org/10.12989/eas.2022.22.4.421.
Chen, Z.Y. (2022), “Neural ordinary differential gray algorithm to forecasting nonlinear systems”, *Adv. Eng. Softw.*, 173. https://doi.org/10.1016/j.advengsoft.2022.103199.
Chen, Z.Y. (2022), “NN model-based evolved control by DGM model for practical nonlinear systems”, *Exp.*

Syst. Appl., 193. https://doi.org/10.1016/j.eswa.2021.115873.
Chen, Z.Y. (2022), "Stochastic intelligent GA controller design for active TMD shear building", *Struct. Eng. Mech*., **81**(1), 51-57. https://doi.org/10.12989/sem.2022.81.1.051.
Chen, Z.Y. (2022), "Systematic fuzzy Navier–Stokes equations for aerospace vehicles", *Aircraft Eng. Aerosp. Technol*., **94**(3), 351-359. https://doi.org/10.1108/AEAT-06-2020-0109.
Chen, Z.Y. (2023), "Grey FNN control and robustness design for practical nonlinear systems", *J. Eng. Res*. (Kuwait), **11**(1), 108-125. https://doi.org/10.36909/jer.11273.
Chen, Z. (2022), "Dynamic intelligent control of composite buildings by using M-TMD and evolutionary algorithm", *Steel Compos. Struct*., **42**(5), 591-598. https://doi.org/10.12989/scs.2022.42.5.591.
Cheng, M. (2009), "Vortex formation and waveform inversion of an internal solitary wave propagating over a shelf-slope topography", *Proceedings of the International Offshore and Polar Engineering Conference*.
Cheng, M. (2011), "Laboratory experiments on waveform inversion of an internal solitary wave over a slope-shelf", *Environ. Fluid Mech*., **11**(4), 353-384. https://doi.org/10.1007/s10652-010-9204-x.
Chiang, W. (2001), "Application and robust H control of PDC fuzzy controller for nonlinear systems with external disturbance", *J. Mar. Sci. Technol*., **9**(2), 84-90.
Chiang, W.L. (2002), "A new approach to stability analysis for nonlinear time-delay systems", *Int. J. Fuzzy Syst*., **4**(2), 735-738.
Chiang, W.L. (2004), "Stability analysis of nonlinear interconnected systems via T-S fuzzy models", *Int. J. Comput. Intel. Appl*., **4**(1), 41-55.
Chiou, D., Hsu, W., Chen, C., Hsieh, C., Tang, J. and Chiang, W. (2011), "Applications of hilbert-huang transform to structural damage detection", *Struct. Eng. Mech*., **39**(1), 1-20. https://doi.org/10.12989/sem.2011.39.1.001.
Eswaran, M. and Reddy, G.R. (2016), "Numerical simulation of tuned liquid tank-structure systems", *Wind Struct*., **23**(5), 421-447. https://doi.org/10.12989/was.2016.23.5.421.
Hsiao, F. (2004), "Decentralized fuzzy control for nonlinear multiple time-delay large-scale systems", *Proceedings of the SICE Annual Conference.*
Hsiao, F. (2005), "Application and robustness design of fuzzy controller for resonant and chaotic systems with external disturbance", *Int. J. Uncertainty, Fuzziness Knowldege-Based Syst.*, **13**(3), 281-295. https://doi.org/10.1142/S0218488505003461.
Hsiao, F. (2005), "Fuzzy control for nonlinear systems via neural-network-based approach", *Int. J. Comput. Method. Eng. Sci. Mech*., **6**(3), 145-152. https://doi.org/10.1080/15502280590923612.
Hsiao, F. (2005), "Fuzzy controllers for nonlinear interconnected tmd systems with external force", *J. Chinese Inst. Engineers*, **28**(1), 175-181. https://doi.org/10.1080/02533839.2005.9670984.
Hsiao, F. (2005), "Robust stabilization of nonlinear multiple time-delay large-scale systems via decentralized fuzzy control", *IEEE T. Fuzzy Syst*., **13**(1), 152-163. https://doi.org/10.1109/TFUZZ.2004.836067.
Hsiao, F. (2005), "Robustness design of fuzzy controllers for nonlinear interconnected systems", *Proceedings of the SICE Annual Conference*.
Hsiao, F. (2005), "T-S fuzzy controllers for nonlinear interconnected systems with multiple time delays", IEEE T. Circuits Syst. I: Regular Papers, **52**(9), 1883-1893. https://doi.org/10.1109/TCSI.2005.852492.
Hsiao, F.H. (2003), "Application and fuzzy H∞ control via T-S fuzzy models for nonlinear time-delay systems", *Int. J. Artif. Intell. Tool*, **12**(2), 117-137.
Hsieh, T. (2006), "A new viewpoint of s-curve regression model and its application to construction management", *Int. J. Artif. Intell. Tools*, **15**(2), 131-142. https://doi.org/10.1142/S021821300600259X.
Hsu, M. (2013), "Routing protocol performance evaluation in wireless ad hoc network", *Inform. Technol. J*., **12**(22), 6595-6599. https://doi.org/10.3923/itj.2013.6595.6599.
Hsu, M.H. (2014), A multi-stage method for deterministic-statistical analysis: A weibo case and measurement studies, https://doi.org/10.4028/www.scientific.net/AMM.519-520.1191.
Hsu, W. (2012), "Risk and uncertainty analysis in the planning stages of a risk decision-making process", *Nat. Hazards*, **61**(3), 1355-1365. https://doi.org/10.1007/s11069-011-0032-1.
Hsu, W. (2014), "A case study of damage detection in four-bays steel structures using the HHT approach", *Smart Struct. Syst*., **14**(4), 595-615. https://doi.org/10.12989/sss.2014.14.4.595.

Hung, C. (2019), “Optimal fuzzy design of chua’s circuit system”, *Int. J. Innov. Comput. Inform. Control*, **15**(6), 2355-2366. https://doi.org/10.24507/ijicic.15.06.2355.

Kuan, F. (2012), “The impact of mood state of information service on purchase intention: A perspective of heuristics”, *Adv. Inform. Sci. Service Sci*., **4**(17), 67-75. https://doi.org/10.4156/AISS.vol4.issue17.7.

Lee, W. (2012), “A hybrid artificial intelligence sales-forecasting system in the convenience store industry”, *Human Factors Ergonomics in Manufact*., **22**(3), 188-196. https://doi.org/10.1002/hfm.20272.

Lin, C. (2014), “Large-area, multilayered, and high-resolution visual monitoring using a dual-camera system”, *ACM T. Multimedia Comput. Commun. Appl*., **11**(2). https://doi.org/10.1145/2645862.

Lin, C. (2015), “Smart monitoring system with multi-criteria decision using a feature based computer vision technique”, *Smart Struct. Syst.*, **15**(6), 1583-1600. https://doi.org/10.12989/sss.2015.15.6.1583.

Lin, C.L. (2009), “Improving the generalization performance of RBF neural networks using a linear regression technique”, *Exp. Syst. Appl*., **36**(10), 12049-12053. https://doi.org/10.1016/j.eswa.2009.03.012.

Lin, J. (2012), “Fuzzy statistical refinement for the forecasting of tenders for roadway construction”, *J. Mar. Sci. Technol*., **20**(4), 410-417. https://doi.org/10.6119/JMST-011-0318-1.

Lin, J. (2012), “Kalman filter decision systems for debris flow hazard assessment”, *Nat. Hazards*, **60**(3), 1255-1266. https://doi.org/10.1007/s11069-011-9907-4.

Lin, J. (2012), “Potential hazard analysis and risk assessment of debris flow by fuzzy modeling”, *Nat. Hazards*, **64**(1), 273-282. https://doi.org/10.1007/s11069-012-0236-z.

Lin, M (2011), “Using GIS-based spatial geocomputation from remotely sensed data for drought risk-sensitive assessment”, *Int. J. Innov. Comput. Inform. Control*, **7**(2), 657-668.

Lin, M. (2008), “A gis-based local spatial autocorrelation for drought risk assessment in arid and semi-arid environments: A case study in ejin oasis, western china”, *Proceedings of the International Geoscience and Remote Sensing Symposium (IGARSS)*. https://doi.org/10.1109/IGARSS.2008.4779851.

Lin, M. (2009), “Fuzzy model-based assessment and monitoring of desertification using MODIS satellite imagery”, *Eng. Comput*., **26**(7), 745-760. https://doi.org/10.1108/02644400910985152.

Lin, M. and Chen, C. (2010), “Application of fuzzy models for the monitoring of ecologically sensitive ecosystems in a dynamic semi-arid landscape from satellite imagery”, *Eng. Comput*., **27**(1), 5-19. https://doi.org/10.1108/02644401011008504.

Lin, M. (2011), “Spatial filtering analysis for quick drought assessment using MODIS images to detect drought affected areas”, *Proceedings of the International Geoscience and Remote Sensing Symposium (IGARSS)*. https://doi.org/10.1109/IGARSS.2011.6049243.

Lin, S.G. (2006), “Modeling ionospheric effects with multiple reference stations for GPS satellite surveying”, *Proceedings of the IASTED International Conference on Modelling and Simulation.*

Liu, K. (2012), “Applying bayesian belief networks to health risk assessment”, *Stochastic Environ. Res. Risk Assessment*, **26**(3), 451-465. https://doi.org/10.1007/s00477-011-0470-z.

Liu, K.F. (2015), “Using fuzzy logic to generate conditional probabilities in bayesian belief networks: A case study of ecological assessment”, *Int. J. Environ. Sci. Technol.*, **12**(3), 871-884. https://doi.org/10.1007/s13762-013-0459-x.

Lu, L. (2003), “Active control for a benchmark building under wind excitations”, *J. Wind Eng. Ind. Aerod*., **91**(4), 469-493. https://doi.org/10.1016/S0167-6105(02)00431-2.

Razavi, A. and Sarkar, P.P. (2018), “Laboratory investigation of the effects of translation on the near-ground tornado flow field”, *Wind Struct*., **26**(3), 179-190. https://doi.org/10.12989/was.2018.26.3.179.

Shen, C. (2011), “A fuzzy AHP-based fault diagnosis for semiconductor lithography process”, *Int. J. Innov. Comput. Inform. Control*, **7**(2), 805-815.

Shih, B. (2012), “NXT information and control on test dimensionality using kolb's innovative learning cycle”, *Proceedings of the 2012 International Symposium on Information Technologies in Medicine and Education, ITME 2012*. https://doi.org/10.1109/ITiME.2012.6291279.

Shih, B. (2013), “An empirical study of an internet marketing strategy for search engine optimization”, *Human Factors Ergonomics in Manufact*., **23**(6), 528-540. https://doi.org/10.1002/hfm.20348.

Tim, C. (2021), “Grey signal predictor and fuzzy controls for active vehicle suspension systems via lyapunov theory”, *Int. J. Comput. Commun. Control*, **16**(3), 3991.

Tsai, C. (2008), "Application of geographic information system to the allocation of disaster shelters via fuzzy models", *Eng. Comput*., **25**(1), 86-100. https://doi.org/10.1108/02644400810841431.

Tsai, C.H. (2007), "A novel delay-dependent condition for time-delay systems", *Proceedings of the IASTED International Conference on Artificial Intelligence and Applications*, AIA 2007.

Tsai, P, and Chen, C. (2014), "A novel criterion for nonlinear time-delay systems using LMI fuzzy lyapunov method", *Appl. Soft Comput. J*., **25**, 461-472. https://doi.org/10.1016/j.asoc.2014.08.045.

Tsai, P. (2015), "Structural system simulation and control via NN based fuzzy model", *Struct. Eng. Mech*., **56**(3), 385-407. https://doi.org/10.12989/sem.2015.56.3.385.

Tsai, P. (2016), "A novel control algorithm for interaction between surface waves and a permeable floating structure", *China Ocean Eng*., **30**(2), 161-176. https://doi.org/10.1007/s13344-016-0009-7.

Tseng, C. (2006), "Optimum arrangement between natural disasters insurance and risk control", *Proceedings of the IASTED International Conference on Modelling and Simulation.*

Wang, R. (2021), "Smart structural control and analysis for earthquake", *Struct. Eng. Mech.*, **79**(2), 131-139. https://doi.org/10.12989/sem.2021.79.2.131.

Wu, J. (2011), "Aerodynamic parameters of across-wind self-limiting vibration", *J. Sound Vib*., **330**(17), 4328-4339. https://doi.org/10.1016/j.jsv.2011.04.026.

Yeh, K. (2007), *Fuzzy control for seismically excited bridges with sliding bearing isolation*, https://doi.org/10.1007/978-3-540-74171-8_47.

Yeh, K. (2008), "Robustness design of time-delay fuzzy systems using fuzzy lyapunov method", *Appl. Math. Comput*., **205**(2), 568-577. https://doi.org/10.1016/j.amc.2008.05.104.

Yeh, K., Chen, C.W. and Chen, C.Y. (2008), "NN robustness design of nonlinear structure systems", *Proceedings of the SICE Annual Conference*. https://doi.org/10.1109/SICE.2008.4654752.

Zandi, Y. (2018), "Computational investigation of the comparative analysis of cylindrical barns subjected to earthquake", *Steel Compos. Struct*., **28**(4), 439-447. https://doi.org/10.12989/scs.2018.28.4.439.

Zhang, Y. (2015), A fuzzy residual strength based fatigue life prediction method", *Struct. Eng. Mech*., **56**(2), 201-221. https://doi.org/10.12989/sem.2015.56.2.201.

Zhen, C.Y. (2020), "Intelligent algorithm and optimum design of fuzzy theory for structural control", *Smart Struct. Syst*., **30**(5), 537-544. https://doi.org/10.12989/sss.2020.30.5.537..

Zhen, C.Y. (2020), "NNDI decentralized evolved intelligent stabilization of large-scale systems", *Smart Struct. Syst.*, **30**(1), 1-15. https://doi.org/10.12989/sss.2020.30.1.001.

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