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Concrete properties prediction based on database

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Abstract. 1078 sets of mixtures in total that include fly ash, slag, and/or silica fume have been collected for prediction on concrete properties. A new database platform (Compos) has been developed, by which the stepwise multiple linear regression (SMLR) and BP artificial neural networks (BP ANNs) programs have been applied respectively to identify correlations between the concrete properties (strength, workability, and durability) and the dosage and/or quality of raw materials'. The results showed obvious nonlinear relations so that forecasting by using nonlinear method has clearly higher accuracy than using linear method. The forecasting accuracy rises along with the increasing of age and the prediction on cubic compressive strength have the best results, because the minimum average relative error (MARE) for 60-day cubic compressive strength was less than 8%. The precision for forecasting of concrete workability takes the second place in which the MARE is less than 15%. Forecasting on concrete durability has the lowest accuracy as its MARE has even reached 30%. These conclusions have been certified in a ready-mixed concrete plant that the synthesized MARE of 7-day/28-day strength and initial slump is less than 8%. The parameters of BP ANNs and its conformation have been discussed as well in this study.

Keywords: concrete; mix proportioning; prediction; database; linear regression; artificial neural network

1. Introduction

For a modern commercial ready-mixed concrete production, a timely accurate performance prediction is very important, which can not only enhance the production efficiency, but also save cost. Forecast technology can be at least applied in two aspects, i.e., (i) the concrete mixtures can be optimized according to the performance prediction, and (ii) in a concrete plant, forecasting can be carried out real-timely according to the actual material consumption for each pallet, thereby improve quality control and prevent quality accident.

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It has been confirmed by a large number of tests that there is a strong linear relationship in ordinary four component concrete (cement, water, fine aggregate and coarse aggregate) between its cement-water ratio and compressive strength. However, when the mineral additives and chemical admixtures such as fly ash, slag and water reducing agent, were added into the concrete, the situation becomes relatively complex (Atici 2011, Chu *et al.* 2013). In many cases, the Bolomy formula was unable to fit the operational accuracy request especially for HSC (high strength concrete) and HPC (high performance concrete). Thus, a new comprehensive empirical relationship must be established (Chen *et al.* 2005, Huang *et al.* 2013). In this study, 1078 sets of mixtures have been collected that the raw materials had different sources. As a reference, the SMLR (linear regression) method has been used for concrete property prediction firstly, and then BP ANNs (back-propagation artificial neural networks) model have been adopted for nonlinear prediction because it is easy to trace the change of fittings and errors, though the other method of SVMs (support vector machines) may be more robust (Cheng *et al.* 2012). The selected concrete properties include 3-day, 7-day, 28-day, and 60-day (56-day) cubic compressive strength, the initial slump and slump flow, and the 28-day and 56-day electric flux.

2. Data collection and pre-processing

8 kinds of raw material have been mixed into sample concrete including water, cement, fly ash, slag, silica fume, fine aggregate, coarse aggregate, and water reducing agent. According to the study of Dias et al. (2001), the optimum models can be obtained from raw data but the non-dimensional ratio does not bring about a good model. In this study, the dosages of the raw materials have been selected as independent variables respectively, and then their key quality indicator (KQI) have also been identified and selected. The number of selected independent variable upto 18 which shown in Table 1. However, not all the selected variables are equally important for different concrete properties; therefore, a rough sets (RS) method (Slowinski 1992) has been adopted for reducing independent variables.

It should be noted that this study followed Chinese civil codes and all the aggregates were taken with absolute dry condition.

Data about the 20-120MPa 28-day cubic compressive strength as well as the 20-270mm initial slump have been measured based on 1078 sets of mixtures. In all the samples, the fine aggregate are natural sand, and the coarse aggregate are crushed stone with nominal maximum size 10-40mm. The solid and liquid content of water reducing agent have been converted to the dosage of fine aggregate and water separately. For convenience to follow-up work, the independent variables are numbered as shown in Table 2.

Table 1 Selected independent variables

Raw material	Selected KQI	Raw material	Selected KQI
Cement	3-day and 28-day compressive strength	Fine aggregate	fineness modulus and silt content
Fly ash	water demand ratio	Coarse aggregate	nominal maximum size, crush index and elongated particles
Slag	7-day and 28-day activity index	water reducer	Air entraining content
Silica fume	-	water	-

Table 2 Number of variables

Variable name	No.	Variable name	No.	Variable name	No.
3-day compressive strength of cement	x_1	Dosage of coase aggregate	x_7	7-day activity index of slag	x_{13}
28-day compressive strength of cement	x_2	Nominal maximum size of coase aggregate	x_8	28-day activity index of slag	x_{14}
Dosage of cement	x_3	Crush index of coarse aggregate	x_9	Dosage of slag	x_{15}
Fineness modulus of fine aggregate	x_4	Elongated particles of coarse aggregate	x_{10}	Dosage of silica fume	x_{16}
Silt content of fine aggregate	x_5	Water demand ratio of fly ash	x_{11}	Dosage of water	x_{17}
Dosage of fine aggregate	x_6	Dosage of fly ash	x_{12}	Air entrained content of water reducer	x_{18}

Table 3 Number of samples for different concrete properties

Property of concrete	3-day strength [MPa]	7-day strength [MPa]	28-day strength [MPa]	60-day Strength [MPa]	Initial slump [mm]	Slump flow [cm]	28-day Electric flux[C]	56-day Electric flux[C]
No. of samples	424	798	923	287	1078	324	246	350

Among the 1078 sets of mixtures, the samples with 28-day compressive strength and/or initial slump are abundant, and the samples with 28-day and 56-day electric flux are relatively fewer. The distribution of different type samples are shown in Table 3. In follow-up analysis, 2/3 of the samples are randomly selected for fitting, and the rest 1/3 are for forecasting. The data used for forecasting are independent from that used for fitting.

3. Stepwise multiple linear regressions

The method of SMLR is relatively simple. The regression coefficients and R^2 value are both shown in Table 4.

As shown in Table 4, there is a certain linear relationship between the concrete properties and dosage and/or quality of raw materials', but the correlationship coefficient is generally low. The maximum values of R^2 are 0.8863 and 0.8682, while the minimum values are only 0.3719 and 0.2809. The values probably could be enhanced if different nonlinear models had been introduced.

4. Simulation and prediction with BP ANNs method

4.1 Artificial neural networks

As a kind of statistical learning algorithms, the artificial neural network (ANNs) primarily is a mimic of biological neural networks. Because of the adaptive nature of interconnected "neurons" , the artificial neural networks can be used to compute values from a large number of inputs and

Table 4 Fitting results using multiple linear stepwise regressions for concrete properties

No. of Vars	Regression coefficient							
	3-day strength	7-day strength	28-day strength	60-day strength	Initial slump	Slump flow	28-day Electric flux[C]	56-day Electric flux[C]
const.	42.2147	7.0068	-5.0692	52.8175	-172.11	101.720	12837.79	587.358
x_1	-0.1467	-0.0455	-0.3287	0	0	-0.6860	-3.4322	0
x_2	0.2009	0.3751	0.4765	0	0.0518	0.2530	0	0
x_3	0.1285	0.1439	0.1548	0.1277	0.2621	0.0324	-8.4832	-0.3672
x_4	0	3.0533	3.7909	1.2527	0	0	0	0
x_5	0	-0.2606	-0.2351	0	0	0	0	0
x_6	-0.0201	0.0081	0.0060	-0.0339	0.2596	0.0017	-10.7437	-2.1282
x_7	-0.0157	0.0026	-0.0010	-0.0047	-0.1111	-0.0316	-4.4804	-0.0268
x_8	-0.0135	-0.1562	-0.1009	-0.5847	0	0.0443	0	0
x_9	-0.2375	-0.3334	-0.3687	-0.8111	-0.9954	-0.5553	-1.6908	0
x_{10}	0.1598	0.1544	0.1180	0.6432	-0.0582	-0.5974	0	0
x_{11}	0.0715	-0.0372	-0.0495	-0.1535	0.0356	-0.3304	50.8840	22.5659
x_{12}	0.0530	0.0547	0.0939	0.0925	0.4570	0.0846	-13.4862	-2.3255
x_{13}	0	-0.0438	0	0	0.5909	0.4253	0	0
x_{14}	0.0056	0.2260	0.2376	0.4248	-0.3010	-0.3244	0	-4.4098
x_{15}	0.0751	0.1137	0.1482	0.1354	0.4004	0.0489	-13.1425	-3.7636
x_{16}	0.2215	0.2329	0.2376	0.2382	0.2210	0.2198	-32.1425	0
x_{17}	-0.0718	-0.1186	-0.0641	-0.1749	-0.2492	0.0263	7.6766	6.9126
x_{18}	-0.2359	-0.3005	-0.2833	-0.1745	0.6537	0.0110	2.8741	3.2909
R^2	0.8199	0.8682	0.8636	0.8863	0.5857	0.3719	0.6063	0.2809

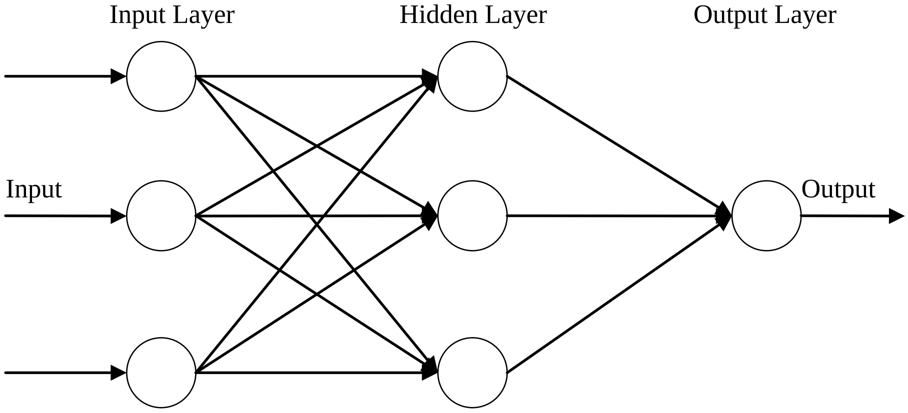


Fig. 1 A typical three-layer back-propagation ANN model

then estimate functions generally unknown, so that it capable of pattern recognition as well as machine learning. Among the ANNs approaches, the back-propagation artificial neural networks (BP ANNs) (Werbos 1974) should be the most popular one, which calculates the gradient of a loss function with respects to all the weights in the network, then the gradient is fed to update the weights, in an attempt to minimize the loss function.

Over the past two decades, the ANNs have been applied in the concrete technology. A number of studies were focused on the feasibility that introduces ANNs to predict concrete properties, and have already got some good results, for example, Dias (2001) pointed out that the neural network models, which can easily incorporate additional model parameters, result in less scatter in predicted values than those given by the multiple regression models. Several different BP network structures have been tested also for prediction of the concrete strength and slump, and it has been found that a 3-layer neural network would give better performance and require less training time, with 18 neuron in the hidden layer (Liu 1997). While the ANNs have been improved by other intelligent method, its efficiency and precision can be enhanced furthermore, for example, while Genetic Algorithm (GA) was used to optimize the weights and thresholds of BP-ANN, a better performance than regression models and BP ANN may be feasible (Yuan 2014). ANN model with the MLP/BP algorithm provides better prediction for shear strength has been reported as well (Amani 2012).

The work of this study mainly focused on the experimental verification, the database application and the development of software platform, The improvement of ANNs algorithm is not the research focus, so that a common three-layer feed-forward ANNs has been adopted, as shown in Fig. 1. While the ANNs have been applied to concrete properties forecasting, a mass data processing is necessary. Most of the previous researchers use commercial software with relatively less sample sets and restricted experiment conditions (Yurdakul 2013). In this study, all the 1078 sets of mixtures come from different concrete plants without any requirements for the origin of raw materials and experiment conditions. A database platform (Compos) has been developed which dedicate to the statistic analysis of concrete mixtures. Carry out comparison or trace the fitting process is convenient by using Compos, and ports for further application has been reserved as well.

In the BP ANNs, The initial quantities were normalized to a range of 0 to 1 via Eq. (1), and then fed into input layer neurons, which in turn pass them on to the hidden layer neuron. The weighted inputs received from each input neuron were added up in hidden layer neuron and associated with a bias, if any, and then the results were passed on through a nonlinear transfer function. The output neuron did the same operation as that of the hidden neuron.

$$X_i = \left(x_i - x_{\min,i}\right) / \left(x_{\max,i} - x_{\min,i}\right) \tag{1}$$

Where $x_{\max,i}$ and $x_{\min,i}$ are the maximum and minimum values of the ith node in the input layer for all the feed data vectors, respectively. The weights were assigned a random value between -1 and 1.

Before it has been applied to any problems, the network should be trained first. The difference between the target output and the calculated model output at each output neuron is minimized by adjusting the weights and biases through some training algorithms. During the training, a neuron receives inputs from a previous layer, weights each input with a prearranged value, and combines these weighted inputs. The combination of the weighted inputs is represented as

$$\mathrm{net}_j = \sum x_i v_{ij} \tag{2}$$

Where net_j is the summation of the weighted inputs of the jth neuron, x_i is the input from the ith neuron to the jth neuron, and v_{ij} is the weight from the ith neuron in the previous layer to the jth neuron in the current layer.

The net_j is passed through a transfer function to determine the level of activation. If the activation of a neuron is strong enough, it produces an output that is sent as an input to other neurons in the successive layer. In this study, sigmoid function is employed as an activation function in the training of the network:

$$f\left(\mathrm{net}_j\right) = 1 \big/ \left(1 + e^{-\mathrm{net}_j}\right) \tag{3}$$

The learning of ANNs is accomplished by a back-propagation algorithm where information is processed in the forward direction from the input layer to the hidden layer and then to the output layer. The objective of a back-propagation network is, by minimizing a predetermined error function, to find the optimal weights that would generate an output vector $Y = \left(y_1, y_2, \cdots, y_p\right)$ as close as possible to target values of output vector $T = \left(t_1, t_2, \cdots, t_p\right)$ with a selected accuracy.

A predetermined error function has the following form

$$E = \sum_P \sum_P \left(y_i - t_i\right)^2 \tag{4}$$

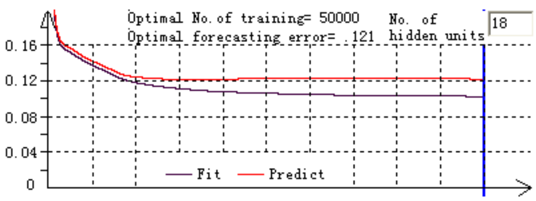
Where y_i is the component of an ANN output vector Y, t_i is the component of a target output vector T, p is the number of output neurons; and P is the number of training patterns.

The least square error method, along with a generalized delta rule, is used to optimize the network weights. The gradient descent method, along with the chain rule of derivatives, is employed to modify network weights as

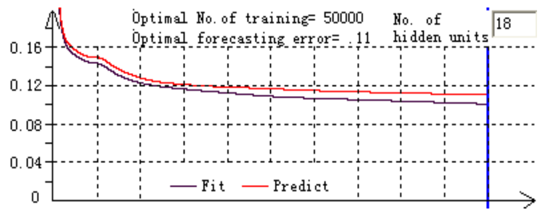
$$v_{ij}^{new} = v_{ij}^{old} - \delta \frac{\partial E}{\partial v_{ij}} \tag{5}$$

Table 5 Average relative error for concrete properties prediction using different network structure

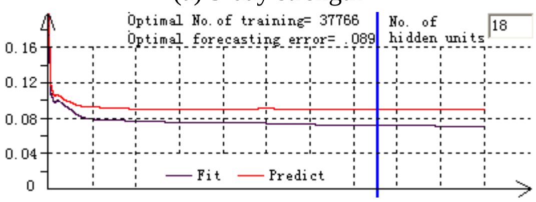
No. of Hidden units	Test Serial No.	3-day Str.	7-day Str.	28-day Str.	60-day Str.	Initial Slump	Slump Flow	28-day Electric flux	56-day Electric flux
6	1	0.128	0.104	0.091	0.080	0.143	0.099	0.226	0.274
	2	0.136	0.111	0.089	0.085	0.142	0.106	0.229	0.279
	3	0.147	0.129	0.089	0.081	0.143	0.099	0.215	0.285
9	1	0.150	0.112	0.089	0.080	0.141	0.108	0.224	0.272
	2	0.137	0.109	0.090	0.084	0.142	0.105	0.223	0.280
	3	0.145	0.118	0.091	0.080	0.137	0.107	0.231	0.314
18	1	0.122	0.109	0.088	0.082	0.137	0.100	0.211	0.293
	2	0.139	0.109	0.089	0.079	0.137	0.102	0.212	0.285
	3	0.145	0.110	0.087	0.079	0.140	0.105	0.213	0.287
36	1	0.146	0.110	0.089	0.083	0.137	0.100	0.206	0.307
	2	0.130	0.117	0.090	0.085	0.139	0.104	0.202	0.285
	3	0.140	0.113	0.090	0.084	0.137	0.099	0.206	0.284



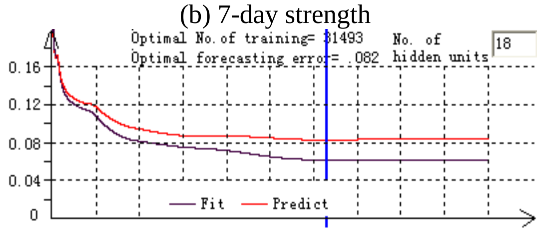
(a) 3-day strength



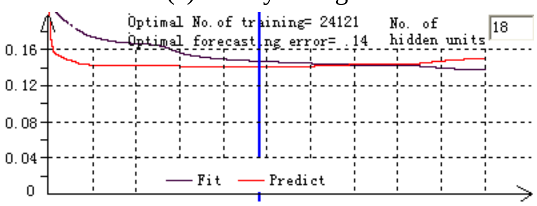
(b) 7-day strength



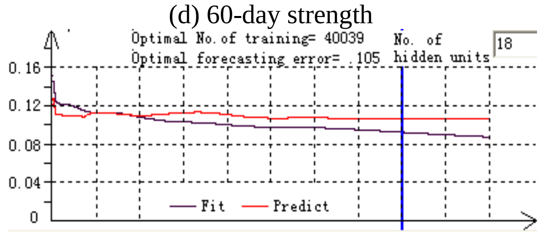
(c) 28-day strength



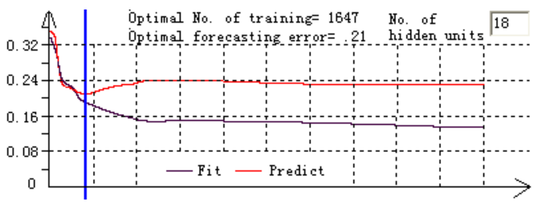
(d) 60-day strength



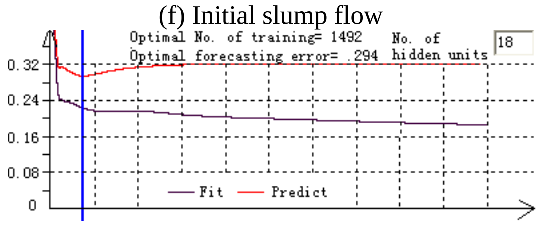
(e) Initial slump



(f) Initial slump flow



(g) 28-day electric flux



(h) 56-day electric flux

Fig. 2 Typical fit-forecasting hydrograph for BP networks

Where δ is the learning rate that used to increase the opportunities for avoiding training process be trapped in a local minima but not a global minima.

4.2 Training and testing of neural network models

The training efficiency of neural network and the forecasting precision are mainly determined by the network structure, particularly the number of middle layer (Akkurt *et al.* 2003). There is no theoretically mature method to determine the suitable number of middle layer so that it is mainly rely on experience at present. The optimum number of hidden layer units is related to the number of input and output units, and the capacity of training sets has obvious effect as well. In this study, different middle layer with 6, 9, 18 and 36 units have been applied respectively as shown in Table 5. Three times repeat have been conducted for every kind of structures to assure the prediction stability of BP network.

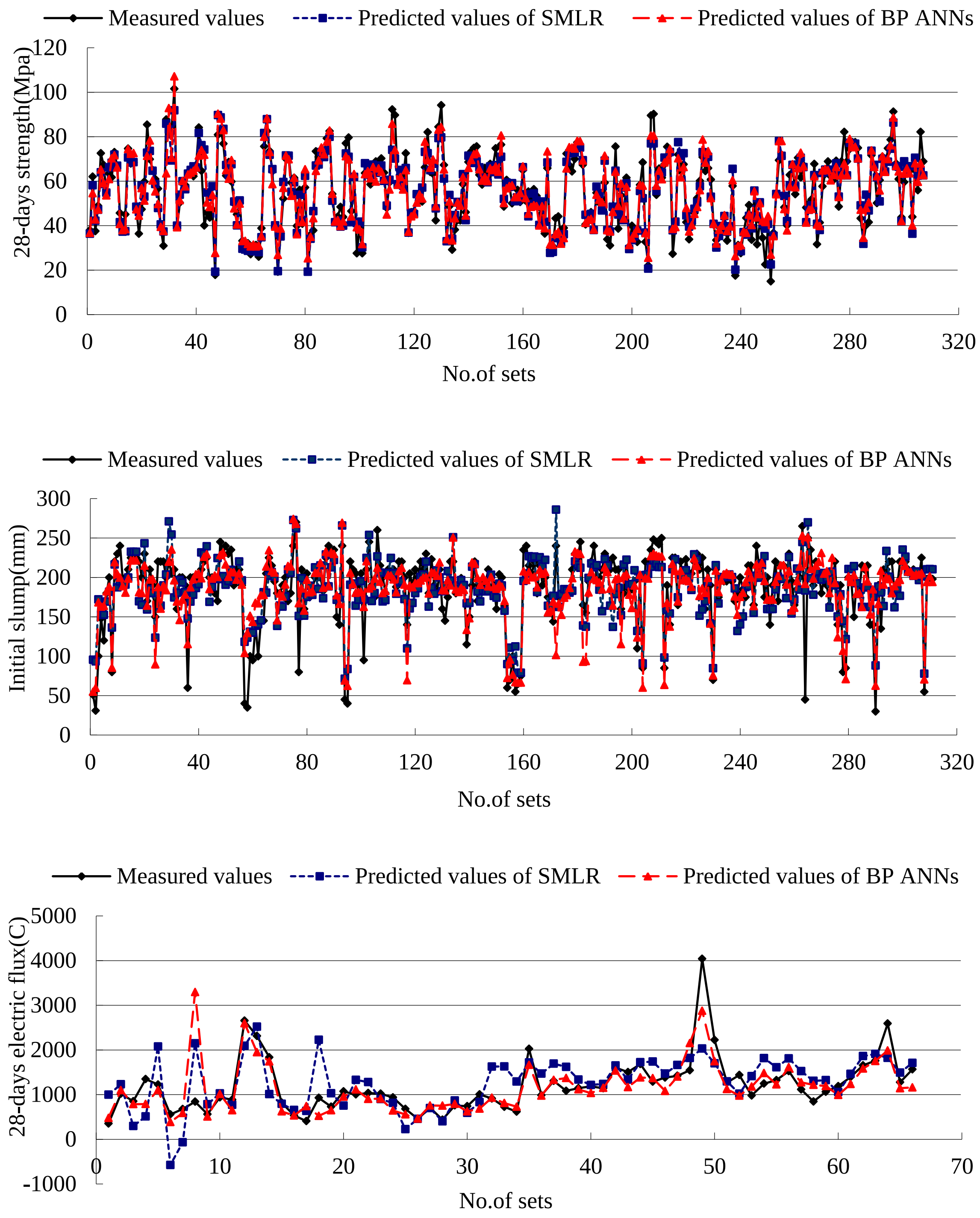


Fig. 3 Contrast of forecasting results using two different methods

Table 6 Forecasting precisions contrast for two models

Concrete properties	R^2		MARE		Qualified points (and Percentage)	
	SMLR	BP ANNs	SMLR	BP ANNs	SMLR	BP ANNs
3-day strength	0.812	0.906	0.167	0.121	78(55.3%)	182(68.4%)
7-day strength	0.868	0.911	0.123	0.110	166(62.4%)	171(64.3%)
28-day strength	0.864	0.884	0.086	0.089	197(64.2%)	283(92.2%)
60-day strength	0.886	0.940	0.089	0.082	54(56.8%)	68(71.6%)
Initial slump	0.586	0.740	0.170	0.140	200(64.3%)	234(75.2%)
Slump flow	0.372	0.579	0.098	0.105	67(62.0%)	83(76.8%)
28-day electric flux	0.606	0.927	0.383	0.213	22(33.3%)	36(54.5%)
56-day electric flux	0.281	0.784	0.441	0.287	16(25.0%)	32(50.0%)

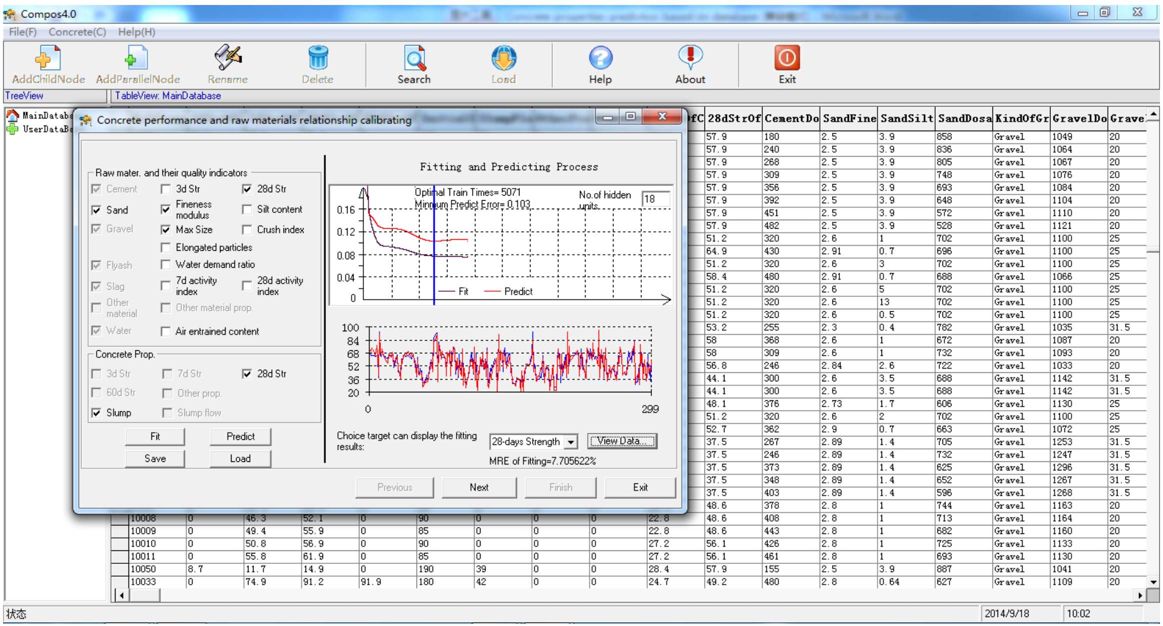


Fig. 4 The interface of compos platform

From Table 5 it could be found that even if the network structure remains the same, the optimal number of training and the forecasting error are unpredictable. The reason largely attribute to the randomness of initial value of weights. Another unsolved problem of BP ANNs is over-fitting which means although the fitting accuracy enhanced unceasingly, but the prediction accuracy did not improve actually. The cause of over-fitting might be the indiscriminately fitting of special or even wrong information for each individual sample. In this study, a skill named “error-tracking tactics” has been used. First of all, the first round of training and forecasting have been carried out, and its predicting error has been taken as initial value of optimal model, then after every training, the prediction are immediately done, if the MARE is less than the initial value, it will be taken as the next round optimal value and record the location, and so on back and forth until the training error or training times reaches a presented value. The typical fit-forecasting processes are shown in Fig. 2, in which the maximum training times and minimum average relative error of every models is 50000 and 0.03 respectively, except for the 56-day electric flux where both optimized points cannot be reached, therefore a maximum training times of 100000 has been used .

It can be found in Table 5 and Fig. 2 that (i) there is no obvious improvement on forecasting accuracy along with the increase of the hidden layer units; 18 units are usually enough for hidden layer. This finding is in accordance with Liu (1997); (ii) the compressive strength have the best prediction results because the MARE for 60-day cubic compressive strength is merely 8%, and its forecast accuracy can rise along with the increasing of age. Forecasting precision for concrete workability takes the second place with its MARE is less than 15%. The forecasting precision for concrete durability is lowest which might be related to the insufficient sample combinations; (iii) the fitting and forecasting results of BP ANNs have shown some uncertainty as it is easy to be trapped into local optimal solution. This situation mainly caused by the random selection of initial network weights. In fact, this problem still does not find a good solution; and (iv) the phenomenon of over-fitting is one of the ubiquitous problems in BP ANNs.

The problem of over-fitting can be partly solved by N-fold cross-validation method(Oh *et al.* 1999), which just splits data into N roughly-equal partitions, and then performs N times analysis which applied on all partitions except for the *K*th for each running, at last the optimal train times can be obtained by averaging the N times of parameter estimations.

5. Comparison of the prediction effect between two models

The forecasting precisions of the two methods have been compared in Table 6, where the forecasting errors within 5 MPa, 25 mm and 15% for compressive strength, initial slump, and other properties respectively have been thought tolerable and then be covered by the safety margin.

Table 6 showed that most of times the BP ANNs model has higher precision and less prediction errors than linear regression model. The contrast of two methods can also be seen in Fig. 3, where the forecasting results of 28-day cubic compressive strength, initial slump, and 28-day electric flux have been plotted respectively.

6. A further verification in a ready-mixed concrete plant

Cixi Mingfeng Building Materials Co. Ltd. is a commercial ready-mixed concrete manufacturer particularly on strength grade C15-C35 pump concrete. A concrete properties prediction and optimization system (Compos) has been developed, as shown in Fig. 4. A concrete performance prediction has been carried out during June to October, 2009. Seven kinds of raw materials have been added into the production, including (i) cement; (ii) fine aggregate; (iii) coarse aggregate; (iv) fly ash; (v) slag; (vi) plasticizer; and (vii) water. Several KQIs are also selected, thereby the total independent variables up to 12. Only three concrete properties—7-day, 28-day cubic compressive strength and initial slump have been considered according to the actual production requirements. There are a total of 163 data sets have been conducted, within them the first 123 sets have been used for modeling and the last 40 sets for predicting. A five-fold cross validation has been used for the BP network modeling. The outcomes of prediction are summarized in Table 7 and Fig. 5.

Table 7 Verification results for production test

Concrete properties	R^2		MARE		Qualified points (and Percentage)	
	SMLR	BP ANNs	SMLR	BP ANNs	SMLR	BP ANNs
7-day strength	0.861	0.882	0.094	0.075	40(100%)	40(100%)
28-day strength	0.910	0.901	0.073	0.061	35(88%)	37(92%)
Initial slump	0.250	0.922	0.106	0.074	25(62%)	36(90%)

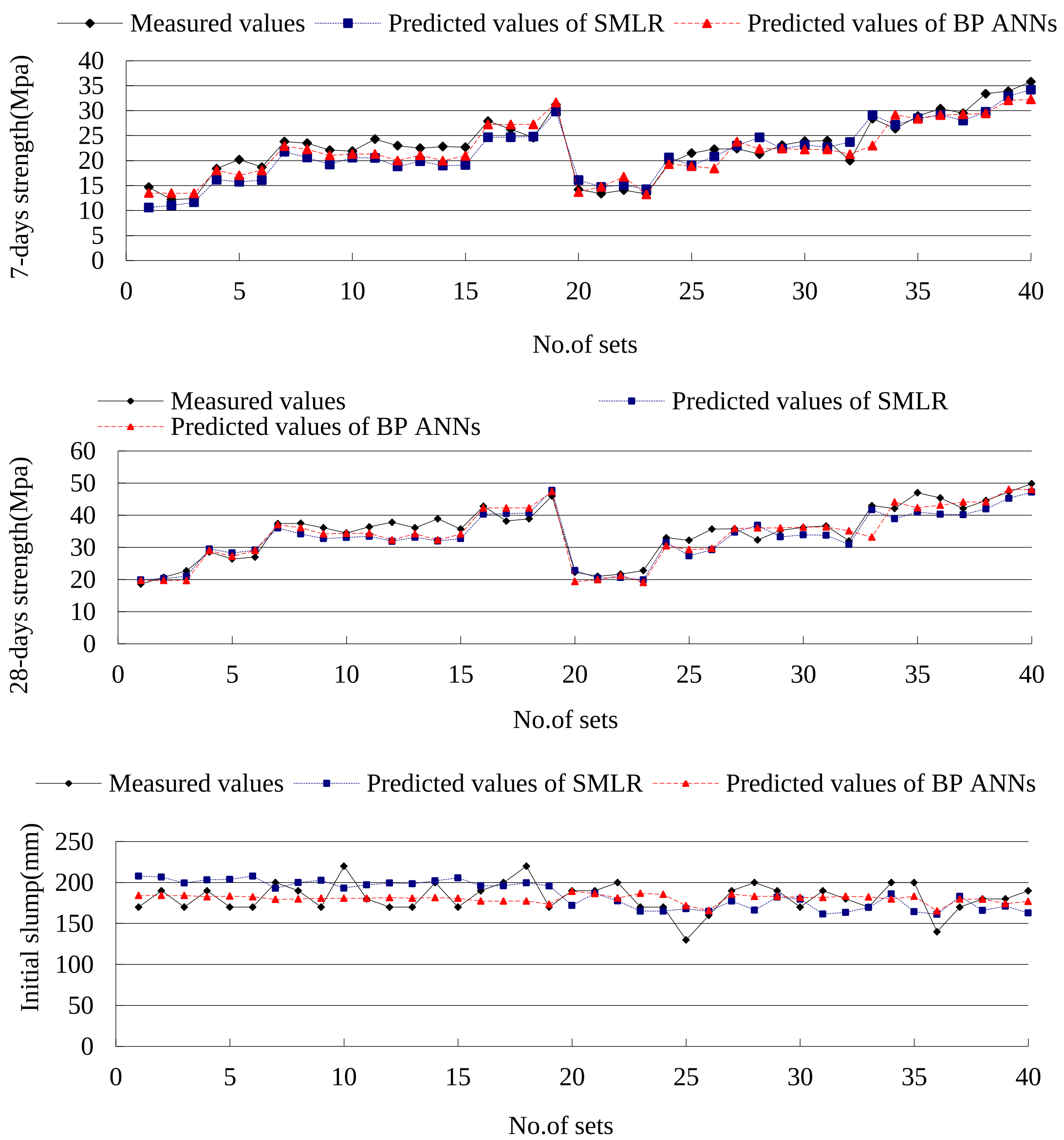


Fig. 5 Contrast of forecasting results using two different methods for production samples

Table 7 and Fig. 5 showed higher forecasting precision for all kinds of concrete performances when the nonlinear method has been used, and the qualified points of prediction are all beyond 90%. It can also be noticed that BP ANNs showed obviously better simulation results in all kinds of prediction indicators than linear method.

Table 8 The summary list of data source projects

No.	Lead of test project	Sources	Time (year)
1	Zheng, Z.Q.	Haimen coal steam-electric plant project, Shantou city, china	2003
2	You, Z.P	Xiamen post telecom hotel project, china	2004
3	Zhang, S.C.	Xiamen Haichang bridge project, china	2005
4	Zhou, J.Q.	Xingguang bridge project in Guangzhou city, china	2006
5	Cai, Y.Z., Wang, W.X. and Bo, X.Z.	Construction of box girder in the Hangzhou bay bridge project, china	2006
6	Shu, Z.P	Construction of box girder in the Hangzhou bay bridge project, china	2006
7	Sun, J.Q.	Bingzhou Yellow river bridge project, china	2006
8	Lin, Z.B. Gao, S. and Liu, W.F. et al.	Construction of basement in People's hospital of Jiangdu city, china	2007
9	Wang, J., Wang, Z.Y., Li, Y.F. and Wang, Y.K.	Ningbo museum project, china	2008
10	Zhang, X.W.	Shijiazhuang-Taiyuan passenger transport line project, china	2009
11	Yu, C.X., Shi, W.K. and Song, Y.X.	New CCTV building project, china	2009
12	Liu, X.L.	Yingde casting yard for Wuhan-Guangzhou passenger transport line project, china	2009
13	Chang, J.G., Wang, S.D. and Zhang, J.H.	Jiaxing-Shaoxing river-crossing bridge project, china	2010
14	Chen, B.L. and Zhang, J.F.	Beijing-Shanghai high speed railway project, china	2010
15	Wan, J.C.	Baidu-city project, Weihai city, china	2010
16	Li, X.	Jinlong modern square project, Anxi city, china	2011
17	Wang, Z.P	Construction of Xijiang river grand bridge in Guangzhou-Zhuhai railway project, china	2011
18	Yu, B.T., Wang, Q.C., Zhou, L.X. and Zhang, F.Q.	The 2nd double line project of Lanzhou-Xinjiang railway, china	2012
19	Luo, Z.Q., Zhang, X.S., Chen, L. And Wu, J.	Yujiabao financial&business district project, Tianjing city, china	2012
20	Wang , J., Cheng, B.J. and Luo, Z.Q. et al.	“117“ building project, Tianjing city, china	2012
21	Wu, C.H.	Construction of tunnels and bridgeworks in Harbin-Dalian high speed railway project, china	2013

7. Conclusions

The following conclusions can be drawn from this work:

- For the concrete with multi-admixtures, there is clearly nonlinear relationship between its compressive strength, workability, and the dosage and/or quality of raw materials'. And the forecasting precision by using nonlinear model is higher than using linear model.

A new concrete properties prediction system based on database (Compos) has been developed, by which the stepwise multiple linear regression (SMLR) and BP artificial neural networks (BP ANNs) programs have been applied respectively to identify correlations between the concrete properties. As mentioned above, Compos can be extending with more applications for concrete quality control, e.g. a typical application is the concrete mixture optimization based on the established prediction model (Yeh 1999). It would be expected to reduce the cost of manufacture.

- There is no obvious improvement on forecasting accuracy of concrete properties along with the increase of the hidden layer units; 18 units are usually enough for hidden layer.

While "error-tracking tactics" were used, the training of network can be ended at an appropriate point, so that over-fitting of network can be avoided to some extent.

- The forecasting precision for concrete compressive strength rise along with the increasing of age as the average relative error for 60-day is usually smaller than 3-day, 7-day and 28-day strength.

In this study, the minimum average relative error (MARE) for 60-day cubic compressive strength was less than 8%. The MARE for concrete workability is less than 15%, and the MARE for durability has even reached 30%.

The Compos platform with BP ANNs method, supported by the "error-tracking tactics" can be used for concrete performance prediction. Although its forecasting results generally displayed certain fluctuations, it can match the demand of actual production.

References

Atici, U. (2011), "Prediction of the strength of mineral admixture concrete using multivariable regression analysis and an artificial neural network", *Expert. Syst. Appl.*, **38**(8), 9009-9618.

Chu, I., Amin, M.N. and Kim, J.K. (2013), "Prediction model for the hydration properties of concrete", *Comput. Concrete.*, **12**(4), 377-392.

Chen, B., Li, F.Q. and Liu, G.H. and Liu, X. (2005), "Study on nonlinear multi-objective optimization algorithm for concrete mix proportions", *J. Zhejiang. Univ. (Eng. Sci.),* **39**(1), 16-19.

Huang, C.H., Lin, S.K. and Chang, C.S. and Chen, H.J. (2013), "Mix proportions and mechanical properties of concrete containing very high-volume of Class F fly ash", *Constr. Build. Mater.*, **46**(9), 71-78.

Cheng, M.Y., Chou, J.S. and Andreas, F.V. and Wu, Y.W. (2012), "High-performance concrete compressive strength prediction using time-weighted evolutionary fuzzy support vector machines inference model", *Automat. Constr.*, **28**, 106-115.

Dias, W.P.S. and Pooliyadda, S.P. (2001), "Neural networks for predicting properties of concretes with admixtures", *Constr. Build. Mater.*, **15**(7), 371-379.

Slowinski, R. (1992), *Intelligent Decision Support: Handbook of Applications and Advances of the Rough Sets Theory*, Kluwer Academic Publishers, Boston.

Werbos, P.J. (1974), "Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences", Ph.D. Thesis, Harvard University.

Liu, J. (1997), "Quality prediction for concrete manufacturing", *Automat. Constr*., **5**(6), 491-499.

Yuan, Z., Wang, L.N. and Ji, X. (2014), "Prediction of concrete compressive strength: research on hybrid models genetic based algorithms and ANFIS", *Adv. Eng. Softw.*, **67**(1), 156-163.

Amani, J. and Moeini, R. (2012), "Prediction of shear strength of reinforced concrete beams using adaptive neuro-fuzzy inference system and artificial neural network", *Sci. Iran. A.*, **19**(2), 242-248

Yurdakul, E.(2013), "Proportioning for performance-based concrete pavement mixtures", Ph.D. Dissertation. Iowa State University.

Akkurt, S., Ozdemir, S. and Tayfur, G. and Akyol, B. (2003), "The use of GA-ANNs in the modeling of compressive strength of cement mortar", *Cement. Concr. Res.*, **33**(7), 973-979.

Oh, J.W., Lee, I.W., Kim, J.T. and Lee, G.W. (1999), "Application of neural networks for proportioning of concrete mixes", *ACI. Mater. J.*, **96**(1), 61-67.

Yeh, I.C. (1999), "Design of high-performance concrete mixture using neural networks and nonlinear programming", *J. Comput. Civil. Eng.*, **13**(1), 36-42.

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