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Predictions of Concrete Compressive Strength Based on a Hybrid Algorithm of GA-BP

Rendong SHI, Wei ZHONG, Hong ZHANG
China Construction West Construction Co Ltd
Sichuan, China
e-mail: 1078154985@qq.com, 19106567@qq.com, 45778136@qq.com

Huangbin CHEN, Xu JI*
College of Chemical Engineering
Sichuan University
Sichuan, China
e-mail: 563360710@qq.com, jxhhpb@163.com

Abstract—**The concrete quality is of great significance for the safety of buildings. This paper conducted the research on this subject in the actual concrete mixing plant, with concrete compressive strength (CCS) being the indicator of concrete quality. Firstly, in order to make the quality evaluation models feasible, the rough set theory method based attribute reduction rule (ARR) was introduced to build the equivalent quality evaluation models with fewer measurable factors. Then, along with the consumptions of raw materials, the correlation coefficients of the consumption amounts, including sand ratio, water-cement ratio, and water-binder ratio,were determined as the input parameters of GA-BP. The prediction accuracy, stability and reliability (*RMSE:1.39; $\bar{X}$: 3.20%; S:2.18%*) were better than those of the contrast schemes. Furtherly, the research shew that the rules of some factors, such as personnel, material properties, equipment status, and environment, are step functions of time, so the time threshold was introduced into GA-BP models to reduce the influence of these factors on the model, the algorithm of determining the optimal time threshold was given. In the case study, the appropriate time threshold improved the accuracy of GA-BP. Finally, the proposed models and the algorithms were applied in the actual plant operations to estimate CCS on line, the satisfied results were achieved.**

Keywords-attribute reduction rule; GA-BP; time threshold; concrete compressive strength

I. INTRODUCTION

As well known, the concrete quality is of great significance for the safety of buildings [1], with concrete compression strength (CCS) being its most important indicator [2]. Now some achievements have been made facing to CCS design optimization[3-6]. But CCS is usually tested three days after production, and sometimes even after 28 days, this makes it impossible for enterprises to take effective measures in the presence of the quality risk [7]. In order to deal with these problems, scholars and engineers have been studying the online and real-time CCS estimation methods[8-13], the maximum error was reduced to 8%. Madandoust.et al. found that the hybrid algorithms were better than the single algorithms, and the models with input layers being closer to the actual production crafts were more conducive to improve the prediction accuracy, the mean relative error was about 4% [14-15], which was an almost acceptable error value considering the characteristics of concrete production. But in a real concrete mixing plant, engineers have to face higher demands, the on-line capacity of concrete quality evaluation and control is the pivotal issue. To this point, the accuracy, confidence and stability of the estimation algorithms are the major challenges, especial for such self-learning algorithms as GA and ANN. This paper will try to rectify this situation facing the changeable production conditions and the limited real data of an actual concrete mixing plant.

II. RESEARCH ON THE ESTIMATION MODELS OF CCS BASED GA-BP

A. The Influence Factors of CCS

The influence factors of CCS are varied and complicated, including material factors (e.g. cement strength, types of additives and fineness of fly ash, etc.), process factors(e.g. mixing method, mixing time, pumping method),equipment factors (automation level, measurement accuracy, etc), environmental factors (climate, temperature, humidity), and personnel factors (skills training, professionalism, performance management, etc) [16-22].

Based on the features of concrete production process, material mixing proportion is the measurable, controllable and critical influence factor for CCS, which could be expressed as continuous functions on time dimension. In terms of the design specification, the design process of concrete mixing proportion begins with calculating water-cement ratio ($R_{w/c}$), water-binder ratio ($R_{w/b}$) and sand percentage R_{sp} according to the target CCS and production conditions[23]. Based on the design process of concrete mixing proportion, the cement dosage is determined by $R_{w/c}$.

Where m_{co} represents the dosage of cement, m_{wa} represents the dosage of water. $R_{w/c}$ is determined by the expected CCS, cement strength and production conditions, which could be evaluated by standard deviation of CCS. In general, the value of $R_{w/c}$ determines the consumption of cement, but PCC is determined by a series of unstructured impact factors, such as the accuracy of weighing equipment, automatic control level, workers skill, and so on, therefore the conventional regression models could not deal with the management issues of CCS. Similarly, the cementitious material dosage is determined by $R_{w/b}$; and the consumptions of sand and rubble are determined by R_{sp} .

In fact, all material dosages are interrelated, and all these intermediate ratios are also important craft parameters for concrete quality, which maybe enlarge or shrink the impacts of influence factors on CCS. But the literature surveying reveals that no researchers have taken these ratios into consideration in the prediction algorithms. So in this paper, the GA-BP model considering the three ratios(R_{sp} , $R_{w/c}$ and $R_{w/b}$) will be built to improve the prediction accuracy of CCS.

Unlike the mixing proportion, the rules of some other qualitative factors, such as material quality, equipment, and environment, are described as step function shown in formula (1) (2). In a certain period of time the CCS function based on the previous regularity is continuous, which could be used to analyze and predict CCS variation trend, but once a time boundary is reached, the quality rules are changed and a discontinuous jump of the quality would occur.

$$\oint_0^t \varepsilon(\tau)d\tau = t\varepsilon(t) \tag{1}$$

$$\varepsilon(t) \overset{\mathrm{def}}{=} \lim_{t\to\infty} r(t) = \begin{cases} f_1(t), & t < 0 \\ f_2(t), & t \geq 0 \end{cases} \tag{2}$$

Where the time boundary t is defined as time threshold, clearly the big value of t is conducive to the stability and confidence of the model results. For concrete mixing plant, the supplying source and the quality of raw materials, equipment cumulative errors, and weather change could influence the time threshold value. Under the background of the present technical situation of concrete mixing plant, strict process management is implemented to improve PCC and make those qualitative factors change smoothly, controllable and predictable. Generally speaking, if the prediction models based on self-learning algorithms can be successfully used in the actual application, the appropriate time threshold is important.

B. The Algorithm of GA-BP

As known, the input layer is very important to the accuracy of ANN. According to the analysis of section 2.1, all factors in Fig.1 should be the input layers of ANN, including qualitative factors and quantitative factors. But ANN cannot deal with qualitative factors directly, so the complex system should be simplified to a quantitative system. In this study, the rough set theory method based on attribute reduction rule (ARR) [28-29] is introduced to meet the above demands. The algorithm of ARR is described simply as fig 1.

The results of ARR are shown in Table 1, indicating that CCS and slump are influenced mainly by the mix proportion, namely the consumptions of the raw materials is made of the equivalent subset. It should be noted that because those factors of method, machine, man and environment have the characteristics of step function of time, remain stable status in a certain time period, so their influence degrees are far less than that of the mix proportion. According to analysis, a three-layer BP neural networks is set up, with the consumptions of the raw materials and their correlation coefficients being input layer, as shown in Fig.2, and the hybrid algorithm of GA-BP is showed in Fig.3

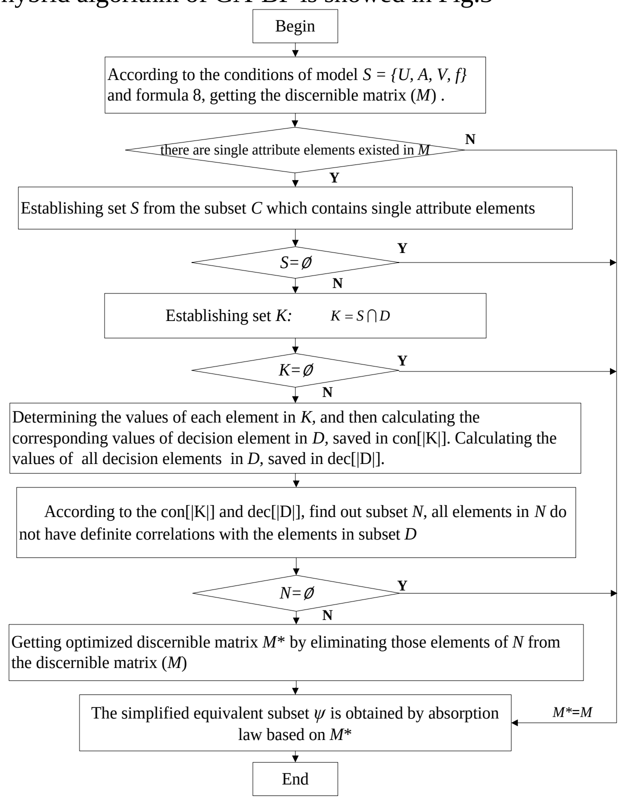

Figure 1. The algorithm of attribute reduction rule.

III. Data Analysis and Results Discussions

In this paper, the case study is based on the actual mixing concrete plant. Total 224 data sets of a single month are extracted from the LIMS database sorted in chronological order, with 11 components (cement, fly ash,..., $R_{w/b}$, R_{sp} , $R_{w/c}$, 28d'CCS). The first 200 datasets are exploited to model training, the last 24 datasets are used to verify the accuracy of the model output, as shown in Table 2.

In order to illustrate the predict accuracy of different input layers schemes, three schemes are built, as shown in Table 3.

Root mean square error (*RMSE*), mean relative error ($\bar{X}$) and error standard deviation (S) are selected as evaluation indexes to evaluate the predictions accuracy and confidence of the models.

RMSE gives a good response to the estimation precision, the smaller the value, the better the accuracy is $\bar{X}$ and S are given to indicate the stability and confidence of the algorithm .The smaller the $\bar{X}$, the smaller the deviation between the real CCS and simulated values. And the smaller S demonstrates the higher stability and reliability of the algorithm. Prediction results are listed in Table 4.

As shown in Table 4, $\bar{X}$ and *S* of the scheme ① are less than that of the other two schemes, the *RMSE* is decreased from 2.18 of ③ to 1.39 of ①. So the scheme ①achieved higher stability and reliability of prediction accuracy compared with the scheme ②, ③. It could be concluded that the correlation between the amounts of raw materials are worth being added to the input layers of GA-BP models.

TABLE I. THE RESULTS OF ARR

$\mu_p(\psi)$	The influencing factors					
	Material	**Method**	**Machine**	**Man**	**Environment**	**Mix ratio**
CCS	0.86	0.72	0.78	0.71	0.76	0.98
Slump	0.72	0.85	0.81	0.76	0.82	0.96
Deli. time	0.85	0.87	0.85	0.83	0.75	0.65
Cost	0.68	0.87	0.76	0.64	0.71	0.87

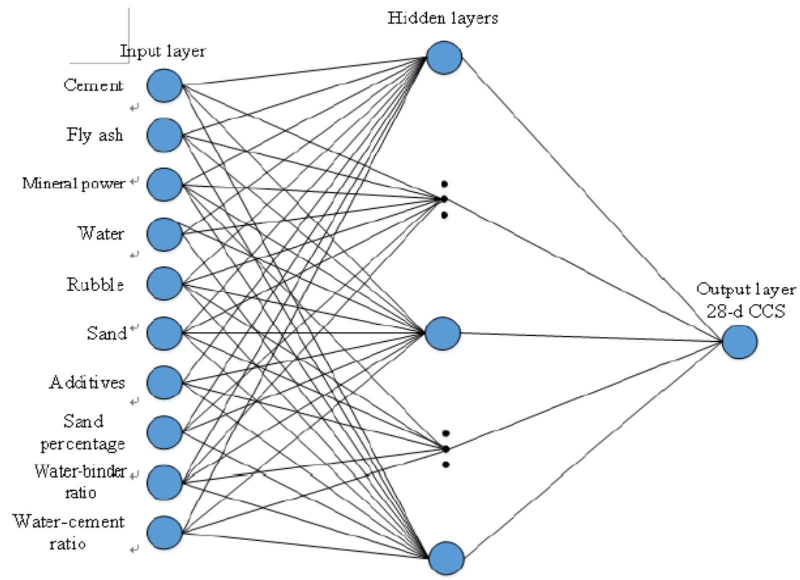

Figure 2. The illustrative diagram of the BP for CCS.

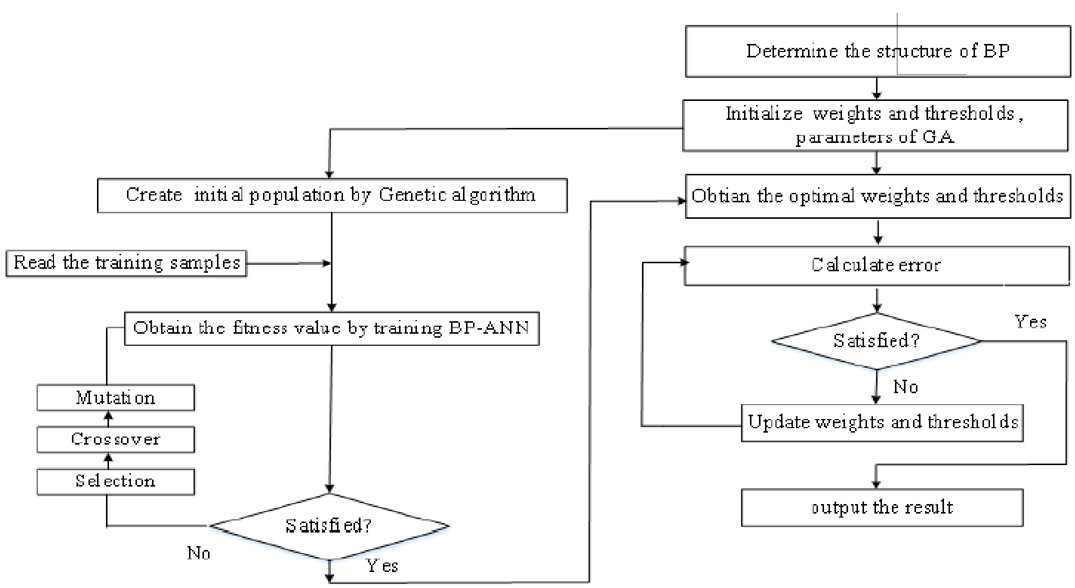

Figure 3. The algorithm of GA-BP.

As previously analyzed, the time threshold is a necessary factor to formulate the regularity pattern of CCS. In order to research on the influence of the time threshold on prediction of CCS, suppose that in a certain period of time the production conditions and the external environment of concrete plant be stable, so the models of CCS are continuous functions. Then the task is to determine the appropriate time threshold. Three schemes with different number of training group, representing different time threshold, are built as shown in Table 5.

As shown in Table 6, *RMSE*, $\bar{\mathbf{X}}$ and *S* of the scheme ① are less than those of the other two schemes, so the scheme ① is more stable and more reliable than the scheme ④⑤. It could be concluded that time threshold is conducive to improve the accuracy of GA-BP. Analyzing the causes, we think that if the time span is greater than the time threshold of the discontinuous factors, the consistency of ANN training is reduced, and thus the prediction precision is reduced. On the contrary, if the time span is too small, overfitting occurs, so the prediction consistency cannot be guaranteed. In the above case, the scheme with 150 datasets from 15 days is the optimum, so the appropriate time threshold (t^a) is 15 days for the plant case.

The models and algorithms developed in this paper have been used in the actual concrete mixing plant in order to help the quality supervisors to estimate CCS in the middle of production process. By means of the method as shown in Fig.4, operators could estimate CCS on the basis of the actual consumption values of the material and the current production status just after the production of every concrete mixer, so that they could find the quality fluctuation early and take corresponding measures.

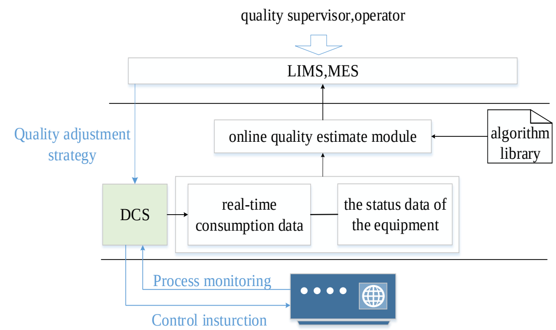

Figure 4. The flow chart of the on-line estimation and correction of concrete quality.

TABLE II. PROJECT DATA

NO	Cement	FA	MP	Rubble	Fresh water	Sand	Recyle-water	Additives	R_{sp}	$R_{w/b}$	$R_{w/c}$	28d'CCS
1	223.5	50.0	71.9	859.0	90.2	871.0	96.3	6.4	0.54	0.50	0.83	34.9
2	213.8	64.6	69.8	1025.0	80.5	798.0	110.3	6.2	0.55	0.44	0.89	30.7
3	214.9	64.6	87.2	1024.0	61.0	784.0	124.3	6.2	0.51	0.43	0.86	34.4
4	214.4	49.6	71.6	885.0	52.5	842.0	119.7	5.9	0.51	0.49	0.80	34.0
…	…	…	…	…					…	…	…	…
224	233.5	49.9	62.1	979.5	160.4	840.2	19.7	6.5	0.52	0.46	0.77	34.3

FA--Fly ash, MP--mineral power. The unit of quantity: the consumption of raw materials-- kg/m^3, 28d'CCS --- MPa; $R_{W/b}$,$R_{W/C}$, R_{sp}-- dimensionless .

TABLE III. THE INPUT LAYERS SCHEMES OF GA-BP

Scheme.	Input layers											Output Layer
①	Cement	FA	MP	Rubble	Fresh water	Sand	Recycled-water	Additives	R_{sp}	$R_{w/b}$	$R_{w/c}$	28d'CCS
②	Cement	FA	MP	Rubble	Fresh water	Sand	Recycled-water	Additives	—	—	—	28d'CCS
③	—	—	—	—	—	—	—	—	R_{sp}	$R_{w/b}$	$R_{w/c}$	28d'CCS

TABLE IV. RESULTS OF THE MODELS

No	Real CCS	Scheme ①		Scheme ②		Scheme ③	
		Simulated	*X*	Simulated	*X*	Simulated	*X*
201	32.2	32.05	0.48%	34.12	5.96%	33.15	2.94%
202	37.9	36.95	2.50%	37.09	2.13%	36.37	4.05%
203	31.6	33.83	7.05%	34.54	9.31%	34.49	9.12%
204	37.5	37.16	0.90%	35.62	5.03%	37.51	0.02%
205	37.2	36.03	3.14%	35.19	5.41%	36.84	0.97%
…	…	…	…	…	…	…	…
222	34.0	32.66	3.94%	33.04	2.83%	33.22	2.31%
223	32.0	33.23	3.83%	34.48	7.75%	34.58	8.05%
224	34.3	34.65	1.02%	34.37	0.20%	33.96	0.99%

TABLE V. THE DATASETS OF THE TRAINING GROUPS

Scheme	Training group	Time threshold	Forecasting group
①	NO. 51-200	15 days	
④	NO. 101-200	10 days	NO. 201-224
⑤	NO. 1-200	30 days	

TABLE VI. RESULTS AND ERROR VALUE OF THE EXPERIMENTS

No	Real CCS	Scheme ①		Scheme ④		Scheme ⑤	
		Simulated	*X*	Simulated	*X*	Simulated	*X*
201	32.2	32.05	0.48%	32.88	2.11%	34.05	5.76%
202	37.9	36.95	2.50%	37.28	1.63%	37.61	0.76%
205	37.2	36.03	3.14%	35.44	4.72%	34.72	6.66%
…	…	…	…	…	…	…	…
222	34	32.66	3.94%	33.09	2.67%	33.77	0.67%
223	32	33.23	3.83%	33.15	3.59%	35.43	10.71%
224	34.3	34.65	1.02%	34.08	0.63%	34.14	0.47%

IV. CONCLUSION

The concrete quality is of great significance for the construction, therefore it is very important to improve the online quality management capability of concrete mixing plant. This paper conducted the study on the above issue in an actual concrete mixing plant.

- The influence factors of concrete quality were studied, and were divided into two kinds of quantitative and qualitative factors. If the all factors were added into the quality evaluation models, the models would be too complicated to be feasible, so the rough set theory method based attribute reduction rule(ARR) was introduced to build equivalent and practicable quality evaluation models with fewer factors. By ARR analysis, $\mu_p(\psi)$ of the mix ratio was 0.98, which was much bigger than the other factors, so the mix proportion of raw materials was determined as the simplified equivalent subset.
- It was found that the consumptions of raw materials affect CCS significantly, meanwhile the correlation coefficients of these consumptions, including sand ratio water-cement ratio, and water-binder ratio, had nearly the same influence degree on CCS. Thus, the three ratio and the material consumptions were determined as the input parameters of GA-BP. The prediction accuracy, stability and reliability (*RMSE*:1.39; $\bar{X}$: 3.20%; *S*:2.18%) of the new model were better than those of the contrast schemes.
- The analysis indicated that some influence factors could be expressed as the continuous functions on time dimension, the others, especial some qualitative factors, such as material properties,

equipment status, and environment, are step functions. So the time threshold was introduced into GA-BP to keep the continuity of the estimation models, and the algorithm of determining the optimal time threshold was given. In the case study, the appropriate time threshold improved the algorithm's accuracy.

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