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Factors affecting the properties of recycled concrete by using neural networks

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Abstract. Artificial neural networks (ANN) has been proven to be able to predict the compressive strength and elastic modulus of recycled aggregate concrete (RAC) made with recycled aggregates (RAs) from different sources. However, ANN is itself like a black box and the output from the model cannot generate an exact mathematical model that can be used for detailed analysis. So in this study, sensitivity analysis is conducted to further examine the influence of each selected factor on the output value of the models. This is not only conducive to the determination and selection of the more important factors affecting the results, but also can provide guidance for researchers in adjusting mix proportions appropriately when designing RAC based on the variation of these factors.

Keywords: artificial neural networks; compressive strength; elastic modulus; recycled aggregate concrete; recycled aggregate; sensitivity analysis

1. Introduction

Appropriate types of construction and demolition (C&D) wastes can be used to produce recycled aggregate (RA), which may be used for recycled aggregate concrete (RAC) production. Recycled aggregates are generally derived from construction debris, such as the demolition of bridges, buildings and airport pavements, so the type of RA which is often characterized by the nature of the attached old cement mortar and the original aggregate used is usually the key component affecting the properties of the RA (Otsuki *et al*. 2003, Etxeberria *et al*. 2007, Gonçalves and de Brito 2010, Deshpande *et al*. 2011). RA may also, besides crushed concrete, contain impurities, such as bricks, tiles, glass, asphalt, plastics, wood, gypsum, clay, etc. Though in small amounts, their presence may serious deteriorate the quality of RA. Taking into account that RAs may be collected from different sources and produced by using different recycling methods (e.g. type and effort of crushers used), the properties of RAs would vary greatly.

Accordingly, concrete made with RAs generally performs poorer than the corresponding natural aggregate concrete (NAC), and the unstable performance of RAs from variable sources with different crushing methods will also cause fluctuations in the properties of RAC. The

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properties of RAC made with high quality RA can be comparable to that of NAC, but those made with poorer RA are relatively weaker and less durable. Such large differences in concrete properties made with different sources of RAs are rarely noticed in concrete made with the "inert" material - natural aggregate (NA). This may be the reason why RA is not commonly used in structural concrete, but as road sub-base or backfilling materials (Bohne and Bratteb 2002).

With increasing interest paid to the research of RAC recently, it is generally realized that reusing RA to replace NA for concrete production can better utilize C&D wastes and save large quantities of natural sources. However, it is based on the condition that the properties of concrete made with RAs can meet the requirements designed for NAC. So it is necessary to accurately assess the characteristics of RAs from different sources, as well as the influence of different sources of RAs on the properties of the new concrete. Unlike NAC, for which mature and reliable design codes and empirical formula have already been established for mix design and prediction of the hardened properties, there is still no standard methods addressing the mix design procedure for RAC, not to mention reliable and generalized models for the prediction of its hardened properties.

As a modeling tool, artificial neural networks (ANN) have been widely used in a variety of engineering applications since the mid-1980s, and it has also been demonstrated to have superior capabilities in modeling more complex relationships.

Sensitivity analysis, an uncertainty analysis technique in relation to quantitative analysis, is a study on assessing how sensitive is the prediction results of the model to the change of the selected input variables. It also determines the significance of these uncertain factors on the results (Khatri and Sirivivatnanon 2004, El-Dash and Ramadan 2006, Zhang and Lounis 2006). For example, by conducting sensitivity analysis, Jain *et al*. (2008) determined the effect of the constituents of concrete mixes to the desired workability.

2. Artificial neural networks

ANN has been more commonly used to predict the properties of NAC (Yeh 2007, Bilgehan and Turgut 2010, Mazloom and Yoosefi 2013) and is rarely adopted for RAC due to the more complex properties of RA. A preliminary study conducted by Duan *et al*. (2013a) constructed an ANN model by utilizing a large amount of published data from a range of sources, including RAs derived from different countries and sources on predicting the 28-day compressive strength of RAC, and the constructed model was able to predict the 28-day compressive strength of RAC quite accurately. Another ANN model established by the same authors for elastic modulus of RAC (Duan *et al*. 2013b) was also capable of producing better predictions than other established correlation equations based on regression analysis.

Through collecting data from different published literatures and dividing them randomly into three groups, with each group acting as the training set, the validation set and the testing set, respectively, the corresponding ANN model can be established. It should be noted that the data number for the latter two sets is no less than 25% of the total data. This was aimed to provide the established model with generalization abilities.

However, ANN is itself like a black box and the outputs from the model cannot be used to provide a mathematical model that can be used for detailed analysis. Also, although it may be easier to construct an accurate ANN model with more factors chosen as input variables, only several main factors are generally considered and tested in preparing concrete mixes by most researchers. In such cases, it is difficult to use the limited data sets collected to construct the ANN model.

Therefore, it seems that it is necessary to make further analysis on the influence of each factor on the output values after the construction of the model.This is not only conducive to determine and select the more important factors affecting the results, but also can provide guidance for researchers in adjusting mix proportions appropriately when designing RAC mixes. Such an analysis is referred to as sensitivity analysis.

3. Sensitivity analysis

Many methods had been tried for sensitivity analysis. Dias and Pooliyadda (2001) adopted a rational approach by carrying out sensitivity analysis to examine how concrete strength would be affected by the input variables, and a Taylor series was used to determine the importance of each factor to the chloride diffusion coefficient of the concrete (Sun *et al*. 2011). Lu *et al*. (2001) analyzed the sensitivity of back-propagation neural networks based on Monte Carlo simulations, and successfully applied the results to some applications. Nyarko *et al*. (2011) identified the most important factors in affecting the damage level of a concrete structure through comparing the networks errors of all possible combinations of the input variables.

4. Research objectives and methodologies

It is not necessary to use ANN to model the effect of RA on the properties of RAC when only one type of RA is used, since in this case the complexity of RA cannot be reflected and the predictive ability of ANN is generally no better than that of the traditional methods like regression analysis.

When RAs from different sources are used, ANN models, which are more capable of modeling complex non-linear relationships, may be more suitable to be adopted for predicting the hardened properties of RAC. The published data of RAs can be divided into two cases: (i) several types of RAs used by a single researcher; (ii) data of RAs from different literature sources used by different researchers. Factors that influence the properties of RAC and used as the input variables of the networks in the two cases are quite different. For the former case, the type of materials other than aggregate, specimen size and operator error are essentially the same, so only the mix proportions and the RA characteristics are chosen as the input variables; while for the latter case, in addition to the mix proportions and RA characteristics, more factors like cement type, specimen size, etc. should be included to establish a generalized model.

A study using data sources described in (i) above has been reported in our previous paper (Duan and Poon 2014a), in which 3 groups with a total of 46 concrete mixes of RAC were prepared with several types of RAs. The experimental results were then used to build the ANN models (Duan and Poon 2014b) for compressive strength and elastic modulus, respectively. Different combinations of factors were selected as the input variables of the networks till the minimum error was reached, and the significance of each aggregate characteristic and the best combinations of factors that would affect the compressive strength and elastic modulus of RAC were finally determined.

The aim of this paper is to examine the relative significance of each of the selected input variable for modeling the compressive strength and elastic modulus of RAC by ANN networks using data sources described in (ii) above. For this purpose, the following steps were adopted in this study.

At first, large amounts of data were collected from different published literatures for constructing the 2 separate networks models for compressive strength and elastic modulus of RAC. 16 factors that might affect the properties of RAC were selected as the input variables of the 2 models. The detailed descriptions of how to convert the qualitative parameters to quantitative indexes was introduced previously (Duan *et al*. 2013b). To ease the analysis, the concrete mix proportions (5 variables) were designated as “certainties”, while the other factors (10 variables) were named as “uncertainties”. The detailed descriptions of the “certainties” and “uncertainties” are shown in Table 1.

Then ANN models for predicting the compressive strength and elastic modulus of RAC were first constructed following the method used previously (Duan *et al*. 2013b). For each model, the network parameters were obtained when the error values reached the minimum. In this study, the mean absolute percentage error (MAPE), the root-mean-squared error (RMS) and the absolut e fraction of variance (R^2) computed by Eqs. (1)-(3), were used as indicators for assessing the performance of the models.

Table 1 Detailed description of the factors that used as input variables of the ANN models

Factors	Input variables	Notations
Certainties	Cement content	C (kg/m^3)
	Water-cement ratio	W/C
	Total aggregate-cement ratio	A/C
	Fine aggregate percentage	S_p
	The mass replacement ratio of NA by RA	$r(\%)$
Uncertainties	Water absorption of coarse aggregate	W_a $(\%)$
	Specific gravity (SSD) of coarse aggregate	SG_{SSD} (g/cm^3)
	Maximum particle size	D_{CA} (mm)
	Impurity content	δ $(\%)$
	Masonry content	m $(\%)$
	Moisture condition of coarse aggregate	k
	Type of natural aggregate	T_N
	Type of recycled aggregate	T_R
	Type of cement*	S_C*
		G_C*
	Specimen size	C_S

*S_C and G_C represent the coefficient depends on the rate of hydration and strength grade of the cement type, respectively. The combination of the two variables is regarded as a factor when conducting sensitivity analysis.

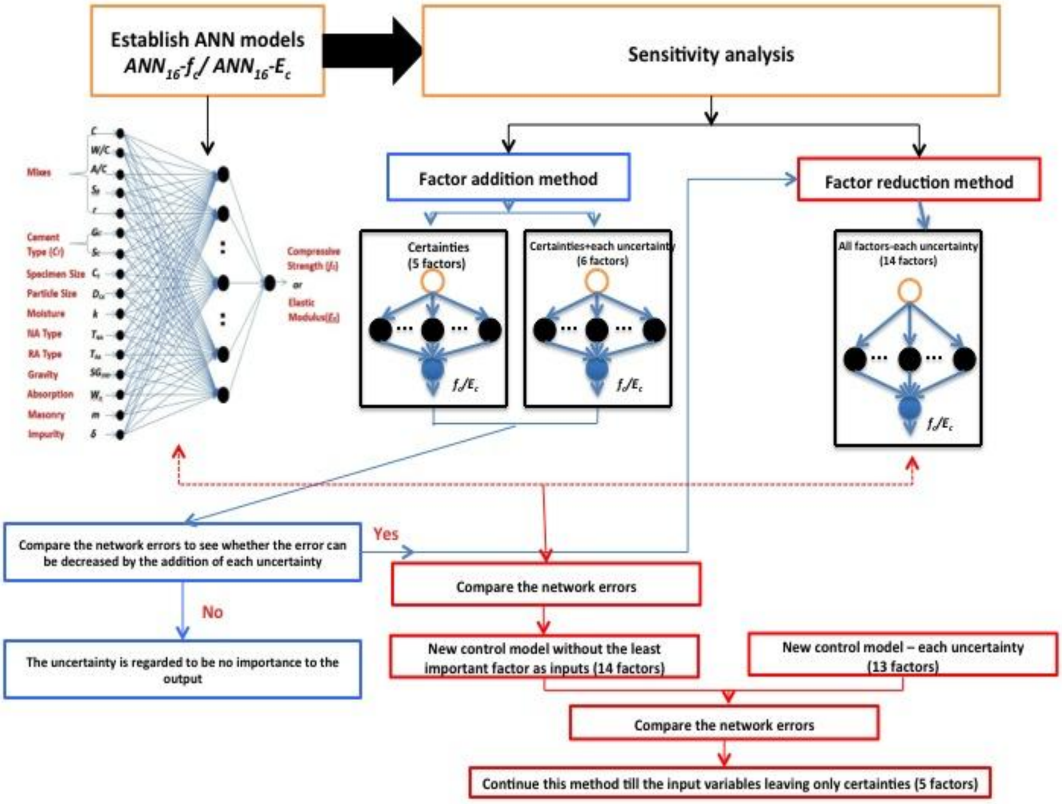

Fig. 1 Flow chart of sensitivity analysis

$$MAPE = \left(\frac{o_j - t_j}{o_j}\right) \tag{1}$$

$$RMS = \sqrt{\frac{1}{p} \times \sum_j \left|t_j - o_j\right|^2} \tag{2}$$

$$R^2 = 1 - \left(\frac{\sum_j \left|t_j - o_j\right|^2}{\sum_j \left(o_j\right)^2}\right) \tag{3}$$

where t and o are the predicted and actual outputs of the network, respectively, and p is the total number of the training and testing patterns. t_j and o_j are the predicted and actual outputs of j^{th} pattern of the network, respectively.

5. Experimental program

5.1 Construction of ANN models

16 factors likely to affect both the compressive strength and elastic modulus of RAC were

analyzed. The factors could be divided into 4 groups: (1) mix proportions of RAC, such as cement content (C), effective water-cement ratio (W/C), total aggregate-cement ratio (A/C), fine aggregate percentage (S_p) and the mass substitution rate of NA by RA (r); (2) aggregate characteristics, such as maximum particle size (D_{CA}), saturated surface dried (SSD) specific gravity (SG_{SSD}), water absorption (W_a) values, masonry (m) and impurity (δ) content, moisture condition (k), NA type (T_{NA}) and RA type (T_{RA}); (3) cement type (T_C), coefficients depend on the strength grade (G_C) and rate of hydration (S_C) of the cement; (4) specimen size (C_S).

324 and 409 data sets collected from 21 (de Juan and Gutierrez 2004, Koulouris 2005, Kou 2006, Dhir and Paine 2007, Hu 2007, Casuccio *et al*. 2008, Kou and Poon 2008, 2011, Yang *et al*. 2008, Bassan *et al*. 2009, Cabo *et al*. 2009, Gomez-Soberon 2009, Zega and Di Maio 2009, Rao *et al*. 2010, Belen *et al*. 2011a,b, Guan 2011, Obispo 2011, Safiuddin *et al*. 2011, Vieira *et al*. 2011) and 23 international published literatures (Ravindrarajah and Tam 1985, Barra and Vazquez 1998, de Pauw and Thomas 1998, Knights 1998, Dhir *et al*. 1999, Gonçalves *et al*. 2004, Poon *et al*. 2004, Kou 2006, Cachim 2007, Dhir and Paine 2007, Ahmed 2009, Kou and Poon 2009, Padmini *et al*. 2009, Rashid *et al*. 2009, Zhou *et al*. 2009, Meddah *et al*. 2010, Corinaldesi 2010, 2011, Belen *et al*. 2011a,b, Guan 2011, Vieira 2011, Kotrayothar 2012), respectively, were used as sample data to construct the initial ANN models for predicting the compressive strength and the elastic modulus of the RAC. For each model, the collected datawere divided randomly into 3 groups as the training, the testing and the validation sets. The testing and the validation sets, no less than 25% of the total data, were aimed to provide the established model with generalization abilities. After training, the optimal models for simulating the compressive strength (ANN_{16}-f_c) and the elastic modulus (ANN_{16}-E_c) were constructed (Fig. 2). The networks architecture and parameters selected are as follows:

- Number of input layer units = 16
- Number of hidden layers = 1
- Number of hidden layer units = 40
- Number of output layer units = 1
- Momentum rate = 0.9
- Learning rate = 0.01
- Learning cycle=15000

Table 2 Performance of ANN models

Sets	Model	R^2	*RMSE*	*MAPE (%)*	Model	R^2	*RMSE*	*MAPE (%)*
Training		0.9955	3.14	5.518		0.9966	1.537	4.152
Testing	ANN_{16}-f_c	0.9912	4.334	6.558	ANN_{16}-E_c	0.992	2.311	5.88
Validation		0.9925	4.048	6.562		0.9918	2.346	6.574
Training		0.986	5.56	9.624		0.9889	2.801	7.845
Testing	ANN_5-f_c	0.98	6.658	11.188	ANN_5-E_c	0.9828	3.41	10.555
Validation		0.977	7.017	12.294		0.9811	3.565	10.408

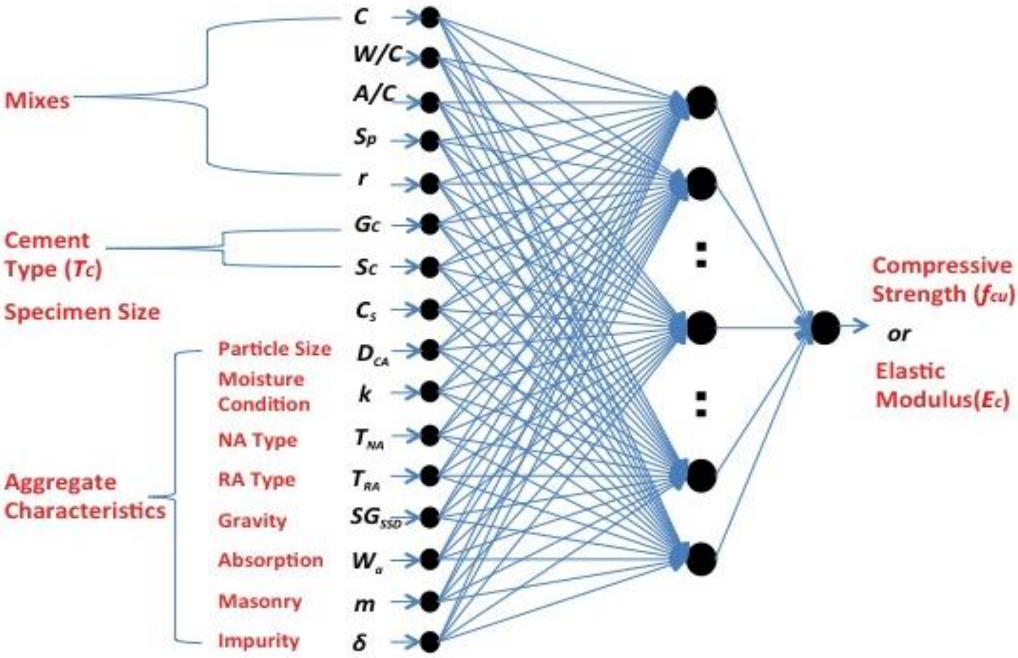

Fig. 2 The constructed ANN models for compressive strength and elastic modulus

5.2 Results and discussion

5.2.1 Performance of ANN models

The performance of the constructed ANN models in predicting the compressive strength (ANN_{16}-f_c) and the elastic modulus (ANN_{16}-E_c) of RAC, as well as a comparison with the models (ANN_5- f_c and ANN_5-E_c) using only the "certainties" as the input variables, are shown in Table 2 and Fig. 3.

As can be seen, the R^2 values of the optimal models (ANN_{16}-f_c and ANN_{16}-E_c) are up to 0.9955 and 0.9966, respectively for the compressive strength and the elastic modulus, indicating that the inputs and the outputs data have good correlations fitted by ANN. These results shown in the testing and the validation sets further prove that both of the optimal models (ANN_{16}-f_c and ANN_{16}-E_c) have strong generalization abilities, and are capable of predicting the compressive strength and the elastic modulus of RAC made with RAs from different sources accurately, with the MAPE values all in the range of 5.8% - 6.6%.

However, when only the "certainties" were used as the input variables, it can be noted that it is nearly impossible for the networks (ANN_5-f_c and ANN_5-E_c) to reach convergence, and the error indexes are also significantly worse than those of the control models (ANN_{16}-f_c and ANN_{16}-E_c), with the MAPE values all exceed 10%.

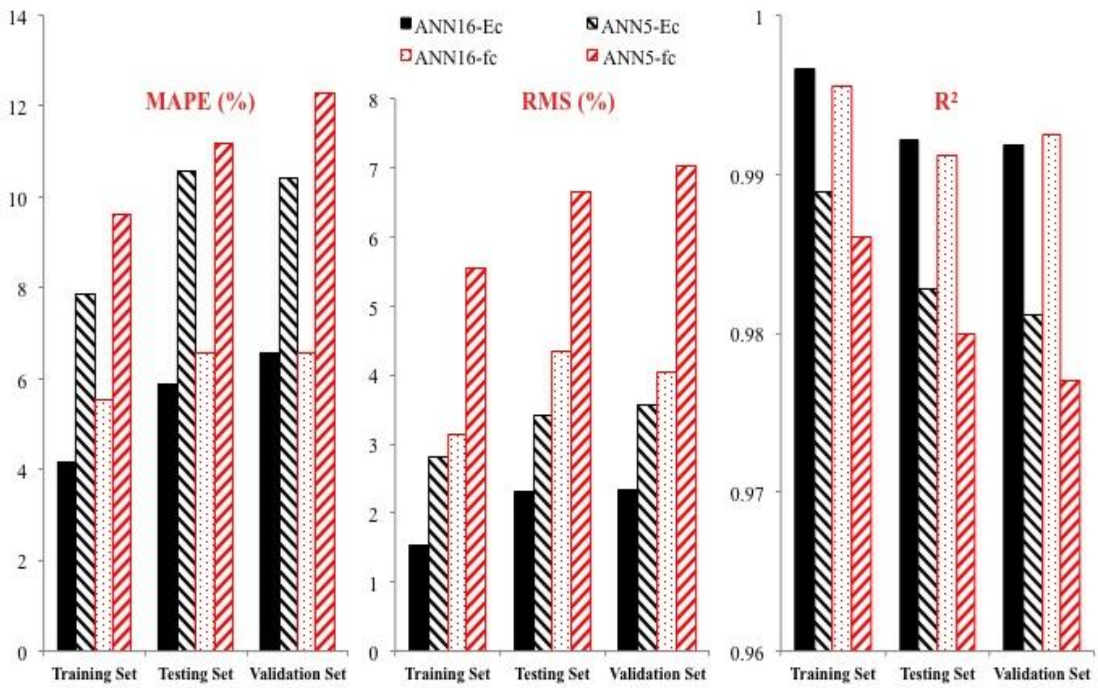

Fig. 3 Performance of the constructed ANN models with all 16 variables and only "certainties" (5 variables) as inputs

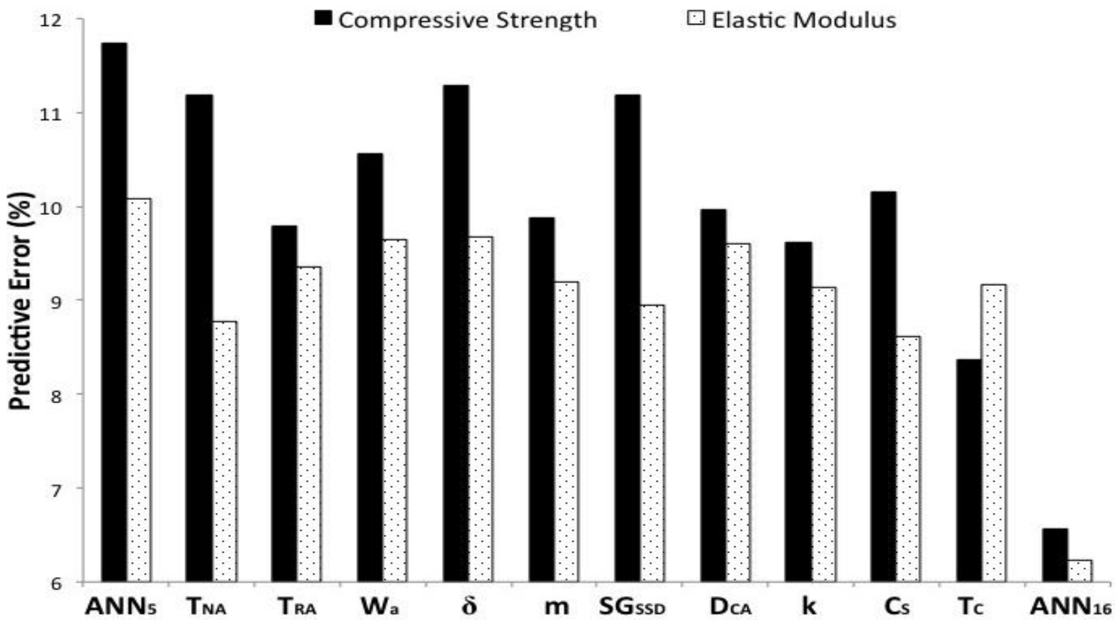

Fig. 4 Influence of each "uncertainty" on the properties of RAC relative to models (ANN_5) with only "certainties" as inputs

Table 3 The errors of network for compressive strength according to FRM (%)

	T_{NA}	T_{RA}	W_a	δ	m	SG_{SSD}	D_{CA}	k	C_S	T_C
ANN_{16}-f_c (**6.56***)	**7.15**	7.42	7.23	7.25	7.43	7.33	7.61	8.02	7.47	7.91
T_{NA}		**7.16**	7.29	7.39	7.67	7.6	7.8	7.89	7.94	7.63
T_{RA}			**7.33**	7.34	7.47	7.36	7.5	8.02	7.74	8.86
W_a				**7.41**	7.54	7.58	8.07	8.13	7.79	8.39
δ					**7.44**	7.6	8.03	7.73	7.6	8.17
m						**7.49**	7.54	7.76	7.87	8.46
SG_{SSD}							**7.78**	7.78	8.41	8.71
D_{CA}								**8.08**	8.15	8.56
k									**8.36**	10.15
C_S										**11.74**

Table 4 The errors of network for elastic modulus according to FRM (%)

	W_a	C_S	δ	m	SG_{SSD}	D_{CA}	T_{RA}	k	T_C	T_{NA}
ANN_{16}-E_c (**6.23***)	**6.09**	6.69	6.52	6.57	6.24	6.44	6.39	6.46	7.14	6.7
W_a		**6.16**	6.39	6.67	6.72	6.2	6.52	6.95	6.72	6.62
C_S			**6.38**	6.68	6.7	6.6	6.94	7.44	8.12	6.87
δ				**6.62**	6.65	6.99	7.21	6.67	7.69	7.9
m					**7.1**	7.17	7.23	7.4	8.05	7.33
SG_{SSD}						**7.25**	7.46	7.83	8.15	8.28
D_{CA}							**7.37**	7.3	8.68	8.77
T_{RA}								**7.44**	8.73	9.46
k									**8.77**	9.17
T_C										**10.08**

For Tables 3-4, the figures with * represent the MAPE value of the control ANN model (ANN_{16}-f_c or ANN_{16}-E_c);
Other figures represent the MAPE value of the networks when the factors, both in the corresponding column and before the corresponding rows, were removed from the inputs of ANN_{16};
Figures in Bold mean that the MAPE value of the networks was the lowest among the corresponding row

5.2.2 Sensitivity analysis

The results of FAM, as shown in Fig.4, indicate that the addition of each uncertain factor is all useful to reduce the predictive error of the networks (ANN_5). Among all the uncertainties, cement type and specimen size are the most effective factor for improving the performance of ANN$_5$-f_c and ANN$_5$-E_c, with a reduction of the MAPE values to 8.36% and 8.62%, respectively. However, their performance can still not comparable with those of the optimal models (6.56% and 6.23%). While it would take a huge amount of time if all the combinations were tried out one by one by using the FAM, so the FRM was adopted to further determine the final importance of each uncertainty.

The detailed results of each of the network by adopting FRM can be noticed in Tables 3-4. For compressive strength (Table 3), the error of the network using all the factors as input variables (ANN$_{16}$-f_c) is about 6.56%. When each "uncertainty" is sequentially excluded from the input variables, the networks error increases slightly to between 7.15% and 8.02%, among which the smallest increase is attained by a combination of factors without NA type as the inputs, and therefore the NA type can be regarded as the least important factor affecting the compressive strength of RAC.

In the next cycle, T_{RA} is experimentally verified as the second least important factor in all the "uncertainties", and its removal from the model only causes a minimal increase of about 0.01% in error value.

Using this method, the "uncertainties" were removed based on their impact on the compressive strength in descending order. As shown in Fig. 5, the orders of importance of the "uncertainties" are as follows:

Cement type - specimen size - moisture condition – maximum particle size - specific gravity (SSD) - masonry content - impurity content - water absorption - RA type - NA type.

It can be concluded that the physical properties of the aggregate, such as aggregate type, water absorption and specific gravity, impurity and masonry content, played relatively minor roles in determining the compressive strength of RAC when compared with the other "uncertainties" like cement type, specimen size, moisture condition and maximum particle size of aggregate used.

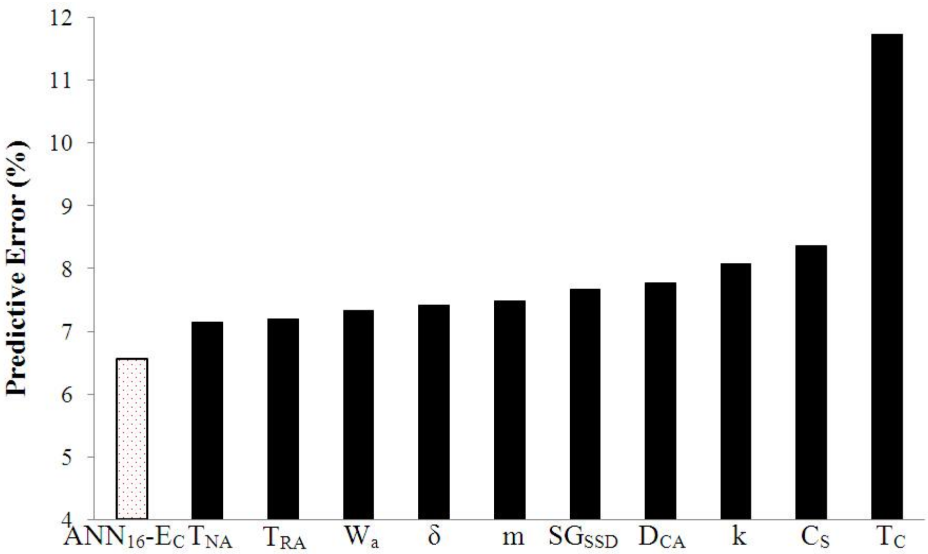

Fig. 5 Errors of network for compressive strength with the remove of "uncertainties" sequentially according to their importance

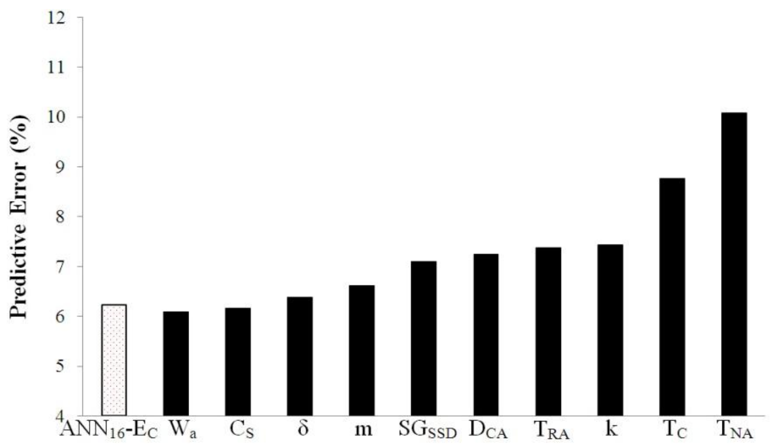

Fig. 6 Errors of network for elastic modulus with the remove of "uncertainties" sequentially according to their importance

While for the elastic modulus (Table 4), the case is slightly different. Firstly, relative to ANN$_{16}$-E_c, the error of the network without using water absorption in the inputs drops slightly to about 6.09%. This may be due to specific gravity of coarse aggregate is able to sufficiently represent the characteristics of RAs for the prediction of elastic modulus. Secondly, it seems that the aggregate type plays a more important role in affecting the elastic modulus than that in the compressive strength prediction.

Besides, the orders of importance of the other "uncertainties" are similar to that for the compressive strength (Fig. 6), and they are:

NA type - cement type - moisture condition - RA type – maximum particle size - specific gravity (SSD) - masonry content - impurity content - specimen size - water absorption.

To sum up, it is better to use all the selected uncertain factors, together with certainties, to constructed ANN models to predict the compressive strength/elastic modulus of RAC made with RAs from different sources, since the lack of any certainty will cause an incomplete mix proportion, while the lack of uncertain may lead to an increase in the predictive error (except W_a for ANN-E_c). Besides, the importance of each uncertainty to the compressive strength is also not completely similar to that to the elastic modulus; this can be used to explain why many established relationships between the elastic modulus of RAC and the corresponding compressive strength are not satisfactory.

The importance of the selected uncertainties to compressive strength/elastic modulus concluded from FAM and FRM is a bit different due to the following reasons: (1) FAM is conducted according to ANN$_5$-f_c/ANN$_5$-E_c, while FRM is based on ANN$_{16}$-f_c/ANN$_{16}$-E_c; (2) FAM is mainly to preliminarily examine whether each selected uncertain factor is reasonable while FRM is to finally determine which combination of factors is optimal and the significance of each "uncertainty" to the compressive strength and elastic modulus, respectively; (3) the use of FRM through removing one uncertainty may be affected by the other uncertain factors, since some of the uncertain factors are closely linked, such as aggregate characteristics. So it is necessary to further examine the importance of each aggregate characteristic to the properties of RAC.

6. Conclusions

- The constructed ANN models (ANN_{16}-f_c and ANN_{16}-E_c) both had strong generalization ability, and were able to predict the compressive strength and elastic modulus of RAC made with RAs from different sources accurately, with the MAPE values all in the range of 5.8%-6.6%.
- The results of the factoraddition method demonstrated that the addition of each "uncertainty" in this study was useful to reduce the predictive error.
- The factor reduction method was able to further assess the importance of each uncertain factor in the ANN model. For compressive strength, cement type and specimen size were the most important factors, and the aggregate moisture content was the most influential factor amongst all aggregate characteristics. While for elastic modulus, although cement type still played an important role, aggregate characteristics like NA type and RA type should also be taken into account.

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Abbreviations

ANN	Artificial neural networks
A/C	total aggregate-cement ratio
C	cement content
C_S	specimen size
C&D	construction and demolition
D_{CA}	maximum particle size
FAM	Factor addition method
FRM	Factor reduction method
G_C	coefficient depends on the strength grade of the cement
k	moisture condition
m	masonry content
MAPE	mean absolute percentage error
NAC	natural aggregate concrete
NA	natural aggregate
r	the mass substitution rate of NA by RA
R^2	absolute fraction of variance
RA	recycled aggregate
RAC	recycled aggregate concrete
RMS	root-mean-squared error
S_c	coefficient depends on the rate of hydration of the cement
S_p	fine aggregate percentage
SG_{SSD}	SSD specific gravity
SSD	saturated surface dried
T_C	cement type
T_{NA}	NA type
T_{RA}	RA type
W_a	water absorption
W/C	water-cement ratio
δ	impurity content

CC