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The Hong Kong Polytechnic University  
Department of Civil and Environmental Engineering

**Modeling the Properties of Concrete Prepared with  
Recycled Aggregates Derived from Different Sources**

DUAN Zhenhua

A Thesis Submitted in Partial Fulfilment of the  
Requirements for the Degree of Doctor of Philosophy

Aug. 2014

## **CERTIFICATE OF ORIGINALITY**

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

**DUAN ZHEN-HUA**

**Abstract of thesis entitled ‘Modeling the properties of  
concrete prepared with recycled aggregates derived from  
different sources’**

Submitted by DUAN Zhen-Hua

for the degree of Doctor of Philosophy

at The Hong Kong Polytechnic University in 2014

**ABSTRACT**

Along with the rapid urban development and economic activities, the generation of construction and demolition (C&D) waste has increased substantially in many parts of the world, in particular in China. In Hong Kong, it has been estimated that the annual generation of C&D waste could be as much as 21 million tons. If not managed properly, such a huge amount of waste will bring significant environmental problem. Since the landfill sites in Hong Kong will be saturated in several years' time, it is important to find a viable way to reuse these waste materials. At the same time, there is critical shortage of natural aggregate (NA) in Hong Kong for the production of new concrete. The concrete industry globally consumes 8-12 billion tons annually of NA,

among them about 4 billion tons are consumed in China. The extraction of NA, such as crushed rock and river sand, has significant impact on the environment. Therefore, the concrete industry is exploring ways to utilize C&D waste for concrete production in order to achieve sustainable development.

Research studies conducted on the recycled aggregate (RA) and the reuse of them in new concrete have found that the properties of RA are generally weaker than those of NA due to the old mortar attached to the RA, reflected in more angular shape, lower bulk and saturated surface dried (SSD) densities, higher water absorption ( $W_a$ ), inferior strength, presence of contaminants (e.g. ceramic) and lower resistance to mechanical and chemical actions when compared with NA. Besides, the properties of concrete made with RA are generally found inferior to those concrete made with only NA due principally to their high absorption and low density, which has hindered its use in the production of concrete in practical application, especially for the concrete with the requirement of durability.

It is encouraging that a large number of literatures have proved that through adopting alternative design and production measures, the properties of concrete made with RA can be comparable with those made with NA. The findings are helpful for the reuse of

RA in new concrete. However, these findings are generally obtained under a relatively ideal situation in the laboratory without considering the case that RAs are generally derived from different sources with vastly different properties. Therefore methods should be developed to provide estimations of the properties of recycled aggregate concrete (RAC) made with different sources and types of RAs.

The aim of this study is to develop a scientific approach for the better prediction of the properties of RAC made with RAs derived from different sources, and a large experimental programme is conducted to verify the validity of the approach.

Firstly, data from different published literatures worldwide were collected as the sample data to construct respective artificial neural networks (ANN) models for predicting the compressive strength and elastic modulus. For each model, factors that may influence the concrete properties were firstly selected and the collected sample data were divided randomly into 3 groups as the training, testing and validation sets, respectively. The data number for the latter two sets is no less than 25% of the total data. This helped to provide the established models with generalization abilities. After training, the optimal models for simulating compressive strength and elastic modulus were constructed, respectively, and the network architecture and parameters were also

determined. Sensitivity analyses were then made to examine the importance of the selected factors, as well as determine which combination of factors could be used to construct the best model.

Then three groups with a total of 46 RAC concrete mixes were prepared to examine the effect of different RAs on the properties of RAC. The RAs used were categorized into 3 groups: (1) RAs derived from laboratory prepared concrete cubes with different compressive strength (35-85 MPa); (2) RAs derived from 3 different sources and crushed by different methods; (3) RAs contained different amounts of added masonry (clay bricks or tiles). As many sources of NAs and RAs are used in these mixes, the aggregate characteristics, such as the fineness modulus (FM) of the fine aggregate, mortar content ( $M_C$ ), 10% fines value (TFV), Aggregate crushing value (ACV), water absorption, SSD specific gravity (SG), impurity ( $\delta$ ) and masonry (m) contents of the coarse aggregate (CA), were quantified. Besides, the mechanical properties of the hardened concrete like compressive strength ( $f_{cu}$ ) and splitting tensile strength ( $f_{tc}$ ), elastic modulus ( $E_c$ ) and durability properties like drying shrinkage and resistance to chloride ion (Cl<sup>-</sup>) penetration were also investigated to examine the influence of different qualities or sources, or different masonry contents of RAs on the properties of RAC. The experimental results of the above mixes were also used as Cases to test

the applicability of the constructed ANN models.

Based on the experimental test results, great variations were noticed in both the properties of RAs derived from different sources and those of the produced RAC.

Also, the traditional relationships established for NAC were found no longer suitable for use in RAC.

The results also indicated that, by constructing ANN models using data collected from many international literatures as sample data, the compressive strength and elastic modulus of RAC made with RAs from different sources could be modeled accurately, with the mean absolute percentage error (MAPE) values all in the range of 5.8%-6.6%.

Besides, it was demonstrated that ANN could be also used to determine the relative importance of the factors in affecting the performance of RAC. It was shown that for compressive strength prediction, cement type and specimen size were the most important parameters, and aggregate moisture condition was the most influential parameter amongst all the aggregate characteristics. For elastic modulus prediction, although cement type still played an important part, the characteristics of the aggregates like types of natural and recycled aggregates used were also critical.

## **PUBLICATIONS ARISING FROM THE THESIS**

This thesis is submitted for the degree of Doctor of Philosophy at The Hong Kong Polytechnic University. The work described in this thesis was carried out by the candidate during the years from 2009 to 2014 in Department of Civil and Environmental Engineering under the supervision of Professor C. S. Poon, the chief supervisor, and Prof. Y.M. Zhang, the co-supervisor.

Nine papers were written by the candidate based on the work presented in this thesis.

### **Academic Journal Papers**

1. **Z.H. Duan\***, S.C. Kou and C.S. Poon (2013), “Prediction of Compressive Strength of Recycled Aggregate Concrete Using Artificial Neural Networks”, *Construction and Building Materials*, Vol. 40, pp. 1200-1206.
2. **Z.H. Duan\***, S.C. Kou, and C.S. Poon (2013), “Using Artificial Neural Networks for Predicting the Elastic Modulus of Recycled Aggregate Concrete”, *Construction and Building Materials*, Vol. 44, pp. 524-532.

3. **Z.H. Duan\*** and C.S. Poon (2014), “Properties of recycled aggregate concrete made with recycled aggregates with different amounts of old adhered mortars”, *Materials and Design*, Vol. 58, pp.19-29.
4. **Z.H. Duan\*** and C.S. Poon (2014), “Factors affecting the properties of recycled concrete by using neural networks”. *Computers and Concrete*, Vol. 14, pp.547-561.
5. **Z.H. Duan\*** and C.S. Poon (2015), “A novel method for assessing the effect of aggregate characteristics on the mechanical properties of recycled aggregate concrete”, submitted to *Cement and Concrete Composites*.

### **Conference Papers**

1. **Z.H. Duan\*** and C.S. Poon (2013), “Approaches for improvement of properties of recycled aggregate concrete”, *The 8th International Symposium on Cement & Concrete. Nanjing, 20-23 September, China*.
2. **Z.H. Duan\***, S.C. Kou and C.S. Poon (2012), “Evaluating the effect of fly ash on the mechanical properties of recycled aggregate concrete by artificial neural networks”, *The 3<sup>rd</sup> National Conference on Recycled Aggregate Concrete, 6-8 Sept, Qingdao, China*.

3. **Z.H. Duan\***, S.C. Kou and C.S. Poon (2012), “Using ANNs to predict the mechanical properties of recycled aggregate concrete prepared with old concrete with different strength grades”, *fib Symposium Stockholm 2012, Conference on Concrete Structures for Sustainable Community, 11-14 June, Stockholm, Sweden.*
  
4. **Z.H. Duan\***, S.C. Kou and C.S. Poon (2010), “Prediction of Compressive Strength of Recycled Aggregate Concrete Using Artificial Neural Networks”, *First International Conference on Sustainable Urbanization on Mini-symposium on Wastes Management and Recycling, 15-17 December 2010, Hong Kong, China.*

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## LIST OF ABBREVIATIONS

<i>ACV</i>	Aggregate crushing value	(%)
<i>AI</i>	Artificial intelligence	-
<i>AIV</i>	Aggregate impacting value	(kN)
<i>ANN</i>	Artificial neural networks	-
<i>A/C</i>	Total aggregate-cement ratio	-
<i>BI</i>	Biological intelligence	-
<i>BNN</i>	Biological neural network	-
<i>BP</i>	Back-propagation	-
<i>BPNN</i>	Back-propagation neural networks	-
<i>C</i>	Cement content	(kg/m <sup>3</sup> )
<i>C<sub>s</sub></i>	Specimen size	-
<i>CA</i>	Coarse aggregate	-
<i>C&amp;D</i>	Construction and demolition	-
<i>CI</i>	Computation intelligence	-
<i>Cl</i>	Chloride ion	-
<i>COV</i>	Coefficient of variations	(%)
<i>CSF</i>	Crushed stone fines	-

$D_{CA}$	Maximum particle size of coarse aggregate	(mm)
$E_c$	Elastic modulus	(GPa)
$EMV$	Equivalent mortar volume	-
$f_{cu}$	Compressive strength	(MPa)
$f_{tc}$	Splitting tensile strength	(MPa)
$FAM$	Factor addition method	-
$FM$	Fineness modulus	-
$FRM$	Factor reduction method	-
$G_C$	Coefficient depends on the strength grade of cement	-
$ITZ$	Interfacial transition zone	-
$LAABV$	Los Angeles abrasion value	(%)
$k$	Moisture state of the coarse aggregate	-
$m$	Masonry content	(%)
$M_C$	Mortar content	(%)
$MAPE$	Mean absolute percentage error	(%)
$NA$	Natural aggregate	-
$NAC$	Natural aggregate concrete	-
$r$	The mass substitution rate of NA by RA	(%)
$R^2$	Absolute fraction of variance	-

<b><i>RA</i></b>	Recycled aggregate	-
<b><i>RAC</i></b>	Recycled aggregate concrete	-
<b><i>RMS</i></b>	Root-mean-squared error	-
<b><i>S<sub>C</sub></i></b>	Coefficient according to the rate of hydration of the cement	-
<b><i>S<sub>p</sub></i></b>	Fine aggregate percentage	-
<b><i>SD</i></b>	Standard deviation	MPa/GPa
<b><i>SG</i></b>	Specific gravity	(g/cm <sup>3</sup> )
<b><i>SI</i></b>	Symbolism intelligence	-
<b><i>SSD</i></b>	Saturated surface dried	-
<b><i>T</i></b>	Curing age	(day)
<b><i>T<sub>C</sub></i></b>	Cement type	-
<b><i>T<sub>NA</sub></i></b>	NA type	-
<b><i>T<sub>RA</sub></i></b>	RA type	-
<b><i>TFV</i></b>	10% fines value	(kN)
<b><i>W</i></b>	Water content	(kg/m <sup>3</sup> )
<b><i>W<sub>a</sub></i></b>	Water absorption	(%)
<b><i>W/C</i></b>	Water to cement ratio	-
<b><i>δ</i></b>	Impurity content	(%)

# **CHAPTER 1: INTRODUCTION**

This chapter aims to give an introduction to this thesis. Firstly, a brief background of this study will be introduced. Then the research objectives of this thesis will be identified. Finally, an overall structure will be given to provide the readability of this thesis.

## **1.1 GENERAL**

As a “shopping paradise”, Hong Kong may leave many good impressions to tourists around the world: the starry Victoria harbor, the skyscrapers, the magnificent Tsing Ma Bridge, and also the beautiful Repulse Bay. However, people may not have noticed that Hong Kong is also facing a number of pressing issues: the highest population density in the world, the increasingly tense housing situation, as well as the dilapidated road, etc.

In this case, Hong Kong is also inevitably facing the problem of disposing urban solid waste. According to the statistics of the quantities of different types of solid waste disposed at various landfills in 1991-2011 monitored by the Environmental Protection Department (EPD, 2013), the proportion of construction and

demolition (C & D) waste almost accounted for a 1/4 (3,340 t/d) of the quantity of the total waste landfilled in 2012. Also, there was an additional about 60,000 t/d of inert construction waste disposed of at public filling areas pending for reuse in reclamation projects. But government figures show that both the public filling areas and landfills are expected to be full by the mid-2010s.

The extraction of natural resources, such as crushed rock and river sand, has significant impact on the environment. Therefore, the concrete industry is exploring ways to utilize C&D waste for concrete production in order to achieve sustainable development.

However, considering that C & D waste may be derived from different sources and activities, such as site clearance, excavation, construction, refurbishment, renovation, demolition and road works, accordingly, the produced recycled materials at a recycling plant from the different sources of wastes, namely recycled aggregate (RA), may be composed of unbound stone, virgin aggregate with attached old mortar, hardened mortar and some impurities, such as bricks and tiles, sand and dust, timber, plastics, cardboard and paper, and metals. Therefore, the properties of RA obtained from different sources may vary

significantly due to the fluctuations in compositions and qualities, making it difficult for them to be reused in the production of new concrete.

## **1.2 RESEARCH OBJECTIVES**

The research objectives of this thesis can be summarized as follows:

- To examine the physical and mechanical properties of different types of RAs.
- To evaluate the effect of different types of RAs on the hardened properties of recycled aggregate concrete (RAC).
- To construct ANN models that can be capable of predicting the compressive strength ( $f_{cu}$ ) and elastic modulus ( $E_c$ ) of RAC accurately.
- To evaluate the importance of the selected input variables on the  $f_{cu}$  and  $E_c$  of RAC, respectively, based on the predicted results.

## **1.3 STRUCTURE OF THE THESIS**

This thesis mainly discusses the use of artificial neural networks (ANN) in modeling the  $f_{cu}$  and  $E_c$  values of concrete made with RAs derived from different sources. The structure of this thesis is presented in eight chapters as follows:

**Chapter 1** gives a brief introduction, the research objectives and the structure of this thesis.

**In Chapter 2**, previous studies on RA and their use in the production of RAC are first reviewed. This is followed by the summarization of the factors that may affect the properties of RAC. Besides, some basic knowledge of ANN and its application in the area of concrete are also reviewed.

**In Chapter 3**, the full study program is introduced. It presents the properties of natural aggregate (NA) and RAs that will be used for concrete production in the laboratory, and also presents the sources of the above aggregates, mix proportions of concrete prepared, as well as the test methods of the concrete properties. Besides, the methodologies of ANN application in this study are also indicated.

**Chapter 4** presents and discusses the experimental results of aggregate characteristics and the properties of hardened concrete made with these aggregates. The influence of different sources of RAs on the properties of concrete is analyzed.

**Chapter 5** examines the validity of using some established relationships to model the  $f_{cu}$  and  $E_c$  of RAC prepared in the laboratory. The predicted results of these relationships are also compared with the experimental test results.

**In Chapter 6**, ANN models are constructed based on the data collected from 5 published literature sources. Then these models are applied to predict the properties of RAC documented in the respective literature: to examine whether ANN is suitable for use in modeling the properties of RAC according to the ANN methods developed by previous researchers, to explore the difference between the use of ANN in natural aggregate concrete (NAC) and RAC, and also to indicate the problems that need to be resolved to provide the constructed ANN model in RAC with generalization ability.

**In Chapter 7**, large amounts (more than 300) of datasets are collected from different published literatures to construct improved ANN models for  $f_{cu}$  and  $E_c$  of RAC, respectively. The improved ANN models are then applied to predict the corresponding properties of RAC prepared in Chapter 4. The predicted results are also compared with the experimental test results. Sensitivity analysis is then

conducted to examine the influence of each input variable on the compressive strength/elastic modulus of RAC after the construction of the models.

**Chapter 8** summarizes the general remarks concluded from the work.

Recommendations for future research on the use of ANN in RAC are then presented.

## **CHAPTER 2: LITERATURE REVIEW**

### **2.1 INTRODUCTION**

Along with the rapid urban development and economic activities, the generation of C&D wastes has increased substantially in many parts of the world, in particular in China. In Hong Kong, it has been estimated that the annual generation of C&D wastes could be as much as 21 million tons (EPD 2013). If not managed reasonably, such a huge amount of waste will bring significant environmental problem. Since the landfill sites in Hong Kong will be saturated in only several years' time, it is important and necessary to find a viable way to reuse these waste materials. At the same time, there is critical shortage of natural aggregate in Hong Kong for the new concrete production. The concrete industry globally consumed 8-12 billion tons annually of natural aggregates (Tu et al. 2006), among them about 4 billion tons were consumed in China. The extraction of natural aggregates, such as crushed rock and river sand, has significant impact on the environment. Therefore, the concrete industry is exploring ways to utilize C&D wastes for concrete production in order to achieve sustainable development.

The literature review mainly contains three parts. In the first two parts, the reviews of studies on the RA and RAC are conducted. While in the last part, basic knowledge of ANN and its application in the area of concrete are reviewed.

## **2.2 RECYCLED AGGREGATE**

### **2.2.1 Introduction**



**Figure 2-1 - Recycled aggregate**

As shown in Figure 2-1, RA used in this study can be regarded as a composite material containing unbound stone, virgin aggregate with attached old mortar, hardened mortar and some impurities. Porous weak mortar may present in RA from some sources, and the amount is dependent on the type and process of

crushers used. Therefore, the original aggregate and the attached old mortar are usually the key components of RA, and the characteristics of RA are determined by the type and quality of original aggregate (Gonçalves and de Brito 2010), as well as both the quality and quantity of the attached old mortar (Otsuki et al. 2003; Oikonomou 2005; Deshpande et al. 2011). Besides, RA may also contain small amounts of impurities, such as bricks, tiles, glass, asphalt, plastic, wood, gypsum, clay, etc. Though the amounts of impurities may be relatively smaller, the presence of them may seriously degrade the quality of RA.



**Figure 2-2 -Pilot C & D Material Recycling Facility in Tuen Mun Area 38 (EDB 2011)**

## **2.2.2 Recycled aggregate**

### ***Recycling technology***

Due to the large volume and complex composition of C&D waste, crushing, sorting and sieving are necessary to produce RA that are suitable for new use.

In Hong Kong, a pilot C&D waste materials recycling plant was established at Tuen Mun by the HKSAR government in 2002 (EDB, 2011), as shown in Figure 2-2. The plant aimed to produce RA for both the use in government projects and works like research and development. The target handling capacity of the facility was about 2,400 t/d. The procedures adopted in this recycling plant (Fong et al. 2004) were as follows:

- A vibrating feeder/grizzly. It is used to sort the hard portions from the collected inert C&D wastes which are suitable for further recycling;
- A jaw crusher (primary crusher). The crusher can reduce the large pieces of sorted materials to smaller sizes, no larger than 200 mm, that can be handled easily by the secondary crushers;
- A magnetic separator. Before the sorted materials are fed into the secondary crushers, the separator is adopted to remove the impurities and clean the materials;
- Cone crushers (secondary crusher). These crushers can further reduce the clean materials into particle sizes no larger than 40 mm;

- Vibratory screens. After screening, various sizes (0-5 mm, 5-10 mm, 10-20 mm and 20-40 mm) of RA can be separated out;
- Storage compartment. It is mainly used for temporary storage of different sized RA.

Additionally, the recycling plant also adopted a prudent quality control method to control the quality of the incoming wastes. Only the materials satisfying the requirement, such as crushed rocks and concrete, were permitted to be processed at the plant. While clay bricks and tiles were generally not allowed to be crushed at the plant. The produced RA crushed after all the processes were also daily sampled and tested.(Fong et al. 2004)

The crushing process plays an extremely important role in affecting the properties of RA (Nagataki et al. 2004;Etxeberria et al. 2007a). Based on the experimental investigation and image analysis, Nagataki et al. (2004) indicated that the quality of RA could be improved through the increase in crushing levels. Relative to the RA that only undergoes one level of crushing, three levels of crushing can produce RA with lower mortar contents, water absorption value ( $W_a$ ), soundness loss and aggregate crushing value (ACV), while with higher

specific gravity value (SG). Besides, they pointed that many levels of processes could improve the aggregate properties through eliminating the particles with micro-defects and irregular voids.

Apart from the RA collected from recycling plants, laboratory prepared old concrete and concrete debris are also usually crushed to produce RA by using hammers or simple crushers. In such cases, it is questionable whether the produced RA can suitably represent RA obtained from the recycling plant (Abbas 2007;Rao et al. 2011).

Besides, the crushing process may sometimes produce voids and cracks in the original aggregate, which may affect the properties of the RA produced (Nagataki et al. 2004). Such voids and cracks may make the RA less resistant to permeation, diffusion, and sulfate ions, etc., leading it poorer in durability properties (Olorunsogo and Padayachee 2002; Somna et al. 2012).

### ***Specifications for the use of recycled aggregate***

Taking into account the study of RA has been carried out from different countries and regions, there are many differences in the corresponding

specifications for the requirements of RA and their applications in concrete. Based on the comparison and analyses of the current standards and specifications for RA, Goncalves and de Brito (2010) concluded that there were two approaches for regulating the use of RA in the concrete production: (1) provide a maximum permissible contents of the incorporation ratio of RA, as well as a maximum permissible replacement ratio of NA by RA in the concrete production, to ensure that the properties of the produced concrete can be comparable with those of the NAC; (2) provide correction coefficients for comparing the RAC and the corresponding NAC with the same strength class, so engineers can adjust the design of structural elements of the concrete made with RA if there are differences between the properties of the two concrete.

In Hong Kong, the specifications requirements for the use of RA are shown in Table 2-1. And there are two sets of specifications governing the use of RA for concrete production (Kou 2006).

- For lower grade applications (C20 concrete), recycled coarse aggregate can be allowed to fully replace NA for concrete production. However, Recycled fine aggregate is not allowed to be adopted to produce the new concrete.

- For Higher grade applications (up to C35 concrete), recycled fine aggregate is still not allowed to be used in the new concrete, and the replacement ratio of natural coarse aggregate by recycled coarse aggregate is limited to no more than 20%; Besides, the produced concrete can be only used for general concrete applications except in water retaining structures.

It can be noticed that, when using RA to prepare new concrete, only the coarse aggregates are allowed. This is mainly due to that recycled fine aggregates normally have very high water absorption capacity, rendering them not suitable for making new concrete (Etxeberria et al. 2007a), since it would lead to excessive drying shrinkage.

**Table 2-1- Specification requirements for recycled aggregate for concrete production in Hong Kong (Fong et al. 2004)**

<b>Requirements</b>	<b>Limit</b>	<b>Test method</b>
Min. dry particle density (kg/m <sup>3</sup> )	2000	BS 812: Part 2
Max. water absorption	10%	BS 812: Part 2
Max. content of wood and other material less dense than water	0.5%	Manual sorting in Accordance with BRE Digest 43
Max. content of other foreign materials (e.g.,metals, plastics, clay lumps, asphalt, glass, tar)	1%	
Max. fines	4%	BS 812: Section 103.1
Max. content of sand (< 4 mm)	5%	BS 812: Section 103.1
Max. sulphate content	1%	BS 812: Part 118
Flakiness index	40%	BS 812: Section 105.1
10% fines value	100 kN	BS 812: Part 111
Grading	Table 3 of BS 882: 1992	
Max. chloride content	Table 7 of BS 8820.05% by mass of chloride ion of combined aggregate	

### ***Residual mortar***

Old cement mortar attached to RA is generally considered as the main cause of poorer properties of RA compared with those of NA (Oikonomou 2005; Butler et al. 2011), reflected in higher  $W_a$ , porosity, ACV and Los Angeles abrasion value (LAAV), and lower SG and 10% fines value (TFV). As a porous material, the porosity of the old cement mortar is mainly determined by the water cement ratio (W/C) adopted by the parent concrete (Nagataki 2000).

The properties of RA obtained from different sources vary significantly due to the fluctuations in the compositions and qualities of the corresponding parent concrete, as well as the quality and quantity of the old attached mortar. It is very difficult to prepare new concrete with an acceptable interface between RA and new paste when the composition of RA is basically weak mortar, since the porosity and absorption of RA are very high in such conditions (Etxeberria et al. 2006).

The amount of residual old mortar is affected largely by the crushing procedures. In general, the more crushing processes are adopted, the more mortar can be separated from the original aggregate. For concrete debris that only undergoes

one level of crushing, the amount of old mortar in RA can be higher than 50% (Nagataki 2004).

The strength of the parent concrete and particle size may also affect the mortar content ( $M_C$ ) of RA. For RA crushed from old concrete (Padmini et al.2009), more  $M_C$  may appear in RA produced from the original concrete with higher strength, for which the bond strength between aggregate and mortar is higher; besides, more  $M_C$  may be present in smaller sized RA particles due to their higher surface areas (Padmini et al. 2009;Domingo et al. 2010).

It is generally agreed that the strength and some other properties of RA can be as good as that of NA if the attached cement mortar can be fully removed. A lot of efforts have been made to study the influence of the attached old mortar on the properties of RA, as well as the ways to remove the mortar, Marta and Gutierrez (2009) found that the  $M_C$  of RA was inversely proportional to its particle size, while proportional to the corresponding  $W_a$ , LAAV and sulphate content.

Abbas et al. (2009) proposed a new method called the equivalent mortar volume (EMV) method. When designing a concrete mix proportion containing RA, they

proposed to account for the relative amount and properties of the two components and adjust both the NA and new paste content of the mix accordingly. The results of the test showed that RAC mixes proportioned by the EMV method satisfied the current requirements for concrete exposed to severe environments. But it is not feasible in practice to calculate the volume of the attached mortar of RAs, since they are seldom derived from a single source before crushing in waste recycling plants.

Apart from the old mortar attached, the angular, rough texture and elongated particle shape of RA are also attributed to its high water absorption capacity.

### ***Particle density***

Due to the presence of attached mortar, the particle density of RA is generally lower than that of the NA (Dhir et al. 1999). For RA that contains certain amounts of masonries, such as bricks and tiles, the particle density will be further decreased.



(a) From old concrete



(b) From recycling plant

**Figure 2-3 - Recycled aggregates from different sources**

Many researchers indicated that the density of RA is related to the quality of the corresponding original concrete from which the aggregate is crushed. Nagataki (2002) indicated that the higher the strength of the parent concrete, the higher the density of the produced RA, of which the attached mortar was assumed the same quantity. Padmini et al. (2009) pointed out that for each particle sized RA produced from old concrete of different strength, the density reduced gradually with an increase in the strength of the original concrete. They indicated that the lower strength concrete was easier to be crushed, and thus more attached mortar could be removed from the aggregate. However, by using hammer to crush five series of old concrete with 28-day compressive strength from 35 MPa to 100 MPa, respectively, Kou and Poon (2012) found that the maximum density attained for 10mm RA and 20mm RA were not those from RA100, but from

RA45 and RA80. This may be due to that it is impossible to produce regular particles, like those produced at a recycling plant, by only crushing using hammer manually.

The density of RA is also dependent on its particle size. As mentioned above, for RAs crushed from old concrete, the smaller the RA size, the higher the percentage was the residual mortar attached to the RA. So higher density may be obtained by RA of smaller size (Padmini et al. 2009; Tam and Tam 2006).

#### ***Water absorption and porosity***

Higher  $W_a$  and porosity, the significant characteristics of RA relative to that of NA, are related to the porous nature of the old mortar attached to RA (Rao et al. 2007). Additionally, the  $W_a$  may be further increased if the RA contains other impurities, such as masonries, wood, clay, etc. The high absorption capacity and porosity are also problems that limit the application of RA in structural concrete.

Due to the high absorption capacity, it is recommended that RA should be pre-wetted or pre-saturated prior to its use in new concrete (Hansen 1992; Etxeberria et al. 2007a). If RA is used in dry condition, it may absorb large

amount of free water quickly during mixing, leading to poorer workability and hardened properties. But through experimental investigation by comparison of the properties of RAC made with RA in different moisture states (oven-dried, air-dried and saturated surface-dried (SSD)), Kou et al. (2004) indicated that RA in an air-dried state was most suitable for preparing normal strength concrete.

The use of multi-levels of crushing can significantly reduce both the absorption capacity and porosity of the RA (Nagataki 2004), since part of the old porous cement paste can be removed from the aggregate.

Similar to the particle density, the  $W_a$  of RA is also affected by the strength of the parent concrete and the particle size. Generally, opposite development trends could be observed when comparing the  $W_a$  with the corresponding density. The higher the parent concrete quality or the smaller the particle size, the lower the  $W_a$  (Padminiet al. 2009; Tam and Tam 2006).

### ***Mechanical properties***

Though indexes like absorption and density are regarded as the most important characteristics of RA (Rao et al. 2011), the mechanical properties also cannot be

ignored. Especially for RA used in structural concrete, the physical, mechanical and durable properties should be all examined (Zega et al. 2010).

The mechanical properties of RA refer its strength, toughness and abrasion resistance. The strength is generally determined by the ACV or TFV test. The toughness and abrasion resistance of aggregate can be characterized by the AIV and the LAAV test, respectively.

With the presence of old weak mortar, the mechanical properties of RA are generally poorer than those of NA due to their higher porosity level and larger amount of cracks (Etxeberria et al. 2006), reflecting in comparatively higher ACV, AIV and LAAV, and lower TFV. Sri Ravindrarajah and Tam (1985) found that the strength of RA played a more important part in affecting high strength concrete when compared with that of low-medium strength concrete. Some researchers (Etxeberria et al. 2007a; Rao et al. 2011) indicated that the failure mode of RAC of medium-high strength was different from that of NAC. For the former, it generally occurred in the RA while for the latter, it usually occurred in the interfacial transition zone (ITZ) between the aggregate and the cement paste.

The mechanical properties of RA are mainly dependent on the quality of the original concrete. Generally, the higher the strength of the parent concrete, the better the mechanical properties of the produced RA (Ajdukiewicz and Kliszczewicz 2002). Some other studies (Paine and Dhir 2010; Kou and Poon 2012) also proved that RA of good quality was suitable for use in high strength/performance concrete.

### ***Impurities***

The presence of impurities may affect the properties of RA seriously, and cause fluctuations in the quality of the corresponding RAC (Dosho 2008).

Due to the varying natures of the original wastes, the types and quantities of impurities present in RAs from different sources may also vary widely (Olorunsogo and Padayachee 2002; Rao et al. 2011). It is necessary to remove the impurities as much as possible prior to the use of RA in new concrete.

### **2.2.3 Technologies for producing high quality of RA**

Due to the poor qualities of RAs caused by the old attached mortar, the vast majorities of RAs worldwide are limited only for using in the road or road-like applications, though they are allowed for structural concrete according to the specifications in many countries (Vazquez, 2013). To resolve this problem, there were attempts to develop technical approaches to improve the quality of RA. Tomosawa and Noguchi (2000) indicated that the quality of RA could be the same level as that of NA if the cement mortar was removed from the virgin aggregate as much as possible. To achieve this objective, some techniques have been proposed as follows:

### ***Conventional recycling process***

As mentioned in Section 2.2.2, the conventional recycling process of RA is similar to that use for natural crushed rock production. By a combination of jaw and cone crushers, large pieces of waste concrete can be crushed to the required particle sizes, and the more the levels of the crushing available, the higher portion of the cement mortar can be removed. Yagishita et al. (1994) indicated that, compared with RA produced by using impact crusher once only, additional or replacement use of roll crushers could improve the quality of RA.

However, the production cost will increase proportional to the level of crushing processes adopted, while the actual yield of the coarse fraction will reduce on the contrary. So it is necessary to find a balance between the level of crushing processes and the requirement of aggregate quality according to the actual application (De Juan and Gutierrez 2009).

### ***Mechanical treatments***

This treatment is to grind and remove the attached mortar from the aggregate particles by means of mechanical forces, such as eccentric-shaft rotor (Yonezawa et al. 2001) and mechanical grinding (Yoda 2003), both of which were developed in Japan. As regards the eccentric-shaft rotor treatment, recycled aggregates after subjected to the primary crusher are immediately fed into the eccentric mill, between the inner and outer rollers, and the coarse aggregate portions are separated from the old mortar through grinding in the rotating mill at a high speed. While for the mechanical grinding, the cement mortar is partially removed from RA through rubbing against iron balls in the numerous of rotating partitioned sections of the drum.

### ***Thermal treatments***

In 1996, Barra (1996) proposed a thermal approach to remove cement mortar from the coarse aggregate by using the thermal stress generated in the weak mortar through several cycles of 2h' heating at about 500 °C and soaking in water.

By means of a rubber hammer, it was demonstrated that some more weak mortar could be further removed, so a combination of thermal with mechanical treatments should be more effective.

### ***Thermal-mechanical treatments***

An improved thermal-mechanical treatment, namely heating and rubbing method (HRM), was then developed by Shima et al. (1999). In the HRM, RA particles are firstly heated at about 300°C for a period of 40 - 60 min, followed by further crushing in a tube mill. The heating would produce fine cracks between the cement paste and the aggregate that make the cement paste more brittle due to dehydration. In such a case, the crushing of heated RA can remove the cement paste more easily.

The energy consumption is a problem for the use of HRM to treat RA, but life-cycle analysis conducted by the same researcher indicated that using HRM could reduce CO<sub>2</sub> emissions by using the HRM powder as cement-related inputs. (Shima 2003, 2005)

### ***Acid soaking treatments***

In 2007, Tam et al. (2007) proposed an acid soaking method, by pre-soaking RAs in three different acidic solutions (HCl, H<sub>2</sub>SO<sub>4</sub>, H<sub>3</sub>PO<sub>4</sub>), to separate coarse aggregate from the cement paste. In this method, RAs are pre-soaked in 0.1 M acidic solutions for 24 h, and then cleaned with water. The authors reported an improvement of RA with a reduction of 7.27-12.17 % in water absorption values after treatment. Besides, they also stated that this method was cost effective to be able to treat about 10 tonnes of RAs with the costs of no more than 500 HKD. Ismail and Ramli (2013) proved the acid soaking method could be used to remove weak mortar on RA surfaces. A linear correlation between the amount of mortar loss and the increase of the molarity of the acid was also reported in the study.

However, there are potential problems that the chloride and sulfate content of RA

may be increased respectively after treatment with the hydrochloric and sulfuric acids. Although the chloride and sulphate contents were reported (Tam et al. 2007) still within the limits according to the respective standards of 0.05% and 1%, and the pH values were still within the alkaline group (above 8.5 pH), it is still a concern that durability problems may be caused by the increase in the chloride and sulfate content of the aggregates.

### ***Microwave treatments***

In 2010, Ong et al. (2010) proposed to use microwave irradiation to separate old attached mortars from the original aggregates in RA. In this method, high different thermal stresses are generated in the porous mortar due to the short-time microwave heating, leading to the formation of grain boundary and embrittlement of the mortar, and finally the mortar lumps cracked into smaller pieces that can be removed easily (Akbarnezhad et al. 2011, Lippiatt and Bourgeois 2012, Choi et al. 2014).

The Microwave treatments have been reported to be quite effective (Quattrone et al. 2014) with no potential durability concerns to the treated RA (Akbarnezhad et al. 2011). But it is yet to be applied in any practical production of RA.

### ***Surface treatments***

In all the above-mentioned treatment methods, due to the high heat or intense mechanical stresses adopted to remove the mortar, the treated RA may be damaged. Also, these treatment methods are energy intensive.

Other researchers have proposed to improve the properties of RA by using surface treatments, such as treatment by polymer (Kou and Poon 2010, Spaeth and Tegguer 2013), treatment by mineral admixtures (Katz 2004, Younis and Pilakoutas 2013), and treatment by nano-materials (Kutcharlapati et al. 2011) and by using microorganisms (Qiu et al. 2014). None of these have been applied in practice in commercial production of RA

## **2.3 RECYCLED AGGREGATE CONCRETE**

There are still many potential problems hindering the widely application of RA in concrete production (Wang et al. 2008) including:

- Lack of standards that can be generally applied to guide the use of RA;
- Few effective and economical processing methods for producing RA that can be used for structural concrete;

- Lack of adequate knowledge concerning the trend of the strength development of RAC;
- Lack of study on the durability of RAC in sever environment.

It is generally accepted that the properties of RAC are inferior to those of NAC.

Sri Ravindrarajah and Tam (1985) attributed the poor properties to the use of RA:

(1) more total porosity of the RAC relative to that of NAC for the large amounts of porous paste within RA; (2) weaker mechanical strength of RA than NA; (3) more amounts of weak bond areas in RAC compared with that of NAC; (4) the effect of multiple cold joints in RA between the new and old mortar.

With increasing attention paid to the research of RA, many experimental investigations of the fresh and hardened properties of RAC have been conducted.

Some of the results are reviewed as follows.

### **2.3.1 Fresh properties**

Generally, concrete mixes made with RA can be designed according to the approach adopted for that made with NA, except that the high absorption capacity of RA must be taken into account to calculate the actual water content.

To obtain the same workability, as reported by many researchers (Hansen and Narud 1983; Sri Ravidrarajah and Tam 1985), concrete made with RA requires about 5% extra water relative to the normal concrete. If same water content is used, the workability of RAC is lower than that of the NAC (Topcu and Sengel 2004). As accepted, the poorer workability of RAC compared with that of NAC could be attributed to the high absorption capacity and porosity of RA, since it may absorb large amounts of water quickly during mixing. While Rashwan and AbouRizk (1997) indicated that the workability of fresh RAC could be affected by the shape and texture of the RA used. Several researchers (Hansen 1992; Sagoe-Crentsil et al. 2001; Etxeberria et al. 2007) have suggested that RA should be pre-wetted or saturated prior to their use in concrete production to improve the workability.

Also, due to the high absorption capacity and porosity of RA, fresh concrete made with 100% RA generally contains higher air contents (Katz 2003).

With respect to the density of the fresh RAC, in which RA with low SG is employed, the value is lower when compared with that of the corresponding NAC. Rao et al. (2007) indicated that the higher air content in the RAC might

further decrease its density.

### **2.3.2 Mechanical Properties**

#### ***Compressive strength***

It has been reported in many literatures (Hansen and Marga 1998; Sri Ravindrarajah et al. 2000; Rahal 2007) that the  $f_{cu}$  of RAC was lower than that of the NAC using the similar mix proportions, due to the poorer quality of RA relative to NA. While the results of some other studies (Dhir et al. 1999; Limbachiya et al. 2000; Limbachiya 2004) indicated that using RA to replace 20-30% NA could still produce concrete with  $f_{cu}$  values comparable and even higher than that of NAC, and thereafter the strength of RAC would reduce gradually with the increase in replacement ratio. The result was verified by the study of Etxeberria et al. (2007a) in which RA was used to substitute 25% NA to produce concrete of medium strength (30-45MPa), and they also recommended that a lower effective W/C and a higher cement content (C) could be adopted for RAC made with 50% or 100% RA to keep the compressive strength same as that of NAC. The findings of Kou and Poon (2012) further demonstrated that RAs from parent concrete of high strength (80-100MPa) could be used to fully replace NA to prepare high performance concrete with mechanical properties equal to

that of NAC.

### ***Splitting tensile strength***

The presence of large amounts of old cement mortar is a main drawback of RA that makes it difficult in producing RAC with properties comparable with those of NAC. However, the attached old mortar can be beneficial to the development of the splitting tensile strength ( $f_{tc}$ ) of RAC, since the residual cement paste can improve the interfacial transition zone (ITZ) between the RA and the new mortar matrix, and thus enhance the bond strength and the  $f_{tc}$  of RAC (Sri Ravindrarajah and Tam 1985; Etxeberria et al. 2007a; Kou and Poon 2008).

While in some other studies, a reduction in  $f_{tc}$  was noticed when RA was used to replace NA for concrete production. Tabsh and Abdelfatah (2009) indicated that the reduction could reach about 25-30% in RAC when compared with that of NAC.

### ***Flexural strength***

The flexural strength of concrete reduced (Ahmed and Struble 1995; Acker 1998; Masood et al. 2001; Bretschneider 2004; Kumutha and Vijai 2010) when RA was

used to substitute NA, and the reduction grew gradually with the increase in the replacement ratio and could reach as high as 50% if 100% RA was used (Kumutha and Vijai 2010). Sri Ravindrarajah and Tam (1985) found that it was difficult to distinguish whether the 28-day flexural strength of RAC was decreased or increased relative to that of NAC. Limbachiya (2004) reported that similar flexural strength to that of NAC could be achieved by concrete made with RA, when the designated strength for both concrete was equal.

### ***Modulus of elasticity***

For structural concrete,  $E_c$  is a very important mechanical index, reflecting the ability of the concrete to resist deformation. It is generally accepted that the  $E_c$  of concrete made with RA is lower than that of concrete made with NA. Corinaldesi (2011) reported that  $E_c$  of RAC made with 30% coarse NA replaced by RA was about 17% lower than that of NAC under the condition of same compressive strength. And the author also pointed out that the reduction in  $E_c$  of RAC relative to that of the corresponding NAC was affected by the particle size of the RA used, and the larger the RA size, the higher the reduction in the  $E_c$  of the produced RAC. Etxeberria et al. (2007) attributed the weak modulus of RAC to the lower modulus of RA relative to that of NA, since the modulus of elasticity

for concrete depends largely on the modulus of aggregate. Though there are many models for predicting the  $E_c$  of NAC, some researchers (Kim et al. 2012) found that these models were no longer suitable for use in calculating the  $E_c$  of RAC, so they also suggested that it was necessary to develop alternative approaches for modeling the  $E_c$  of RAC.

### ***Drying shrinkage and creep***

Due to the presence of old porous mortar in RA, the drying shrinkage and creep of concrete made with RA are generally higher than those of the corresponding NAC. A study conducted by Domingo et al. (2010) showed significantly higher creep and shrinkage values were recorded for RAC, and were about 70% and 50% exceeded those of the corresponding NAC, respectively. Limbachiya et al. (2000) reported that the higher shrinkage and creep values of RAC relative to conventional concrete could be partly due to the more cementitious material used in RAC, since when designing the mix proportions of RAC with the 28-day strength equal to that of the NAC, the cement quantity was sometimes increased and thus the effective W/C was reduced accordingly. Kou et al. (2011) attributed the higher shrinkage of RAC to both the presence of old cement paste in RA and its lower stiffness. While Sri Ravindraiah and Tam (1985) explained the higher

shrinkage of RAC for the combined efforts of higher proportions of shrinkage mortar and increased quantity of free water, and they also indicated that the higher designated strength the RAC, the greater the increase in drying shrinkage. Gomez-Soberon (2002) found a proportional relationship between the increase in the shrinkage of RAC and the replacement ratio of NA by RA, and the author also found that the shrinkage rate of RAC was much rapid at early ages, and thereafter slowed down with time. Besides, the author suggested that the use of RA to replace no more than 30% NA could be capable of producing 'good' concrete without the use of shrinkage inhibitors.

Sri Ravindrajah and Tam (1985) attributed the higher creep of RAC relative to that of NAC to two reasons: (1) the decrease in restraint to volume changes of the cement paste by the aggregate of lower modulus;(2) the higher proportions of creeping mortar. Some researchers (Sri Ravindrajah and Tam 1985; de Pauw et al. 1998; Limbachiya et al. 2000) reported that the creep coefficient values of RAC were dependent largely on the strength of the parent concrete, and the values reduced with the decrease in the strength.

### ***Durability***

The long-term durability problems are the primary reasons that hamper the application of RA for structural use (Tu et al. 2006; Etxeberria et al. 2007b).

Permeability, carbonation, freeze-thaw resistance, and sulphate resistance are some main indexes that used to evaluate the durability properties of RAC.

Poorer durability properties were noticed in RAC when compared with those in NAC by the study carried out by Olorunsogo and Padayachee (2002), in which the chloride conductivity and water sorptivity of RAC both increased with the increase in the replacement ratio of NA by RA. The authors attributed these to the cracks and fissures formed in RA during the crushing processes.

The experimental results of Limbachiya et al. (2000) showed that coarse RA crushed from rejected precast elements could be used to replace NA to produce high performance concrete with comparable durability properties, such as resistance to chloride diffusion, chloride-induced corrosion, freeze/thaw and abrasion, to the corresponding conventional concrete.

It was suggested that the replacement of cement by appropriate amounts of mineral admixtures, such as fly ash, ground granulated blast furnace slag, silica

fumes and metakaolin, could be capable of improving the durability properties of RAC (Kou et al. 2011), since these admixtures are helpful to form optimal gel, modify pore structure, and improve the microstructure of the ITZ as well as the bond strength between the new cement paste and RA.

Kou and Poon (2010) proposed an approach to enhance the durability properties of RAC by the impregnation RA with polyvinyl alcohol solution, and they concluded that the durability properties of concrete made with such RA were improved, with the drying shrinkage values decreased and resistance to chloride penetration enhanced to levels similar to those of NAC.

### **2.3.3 Factors that may affect the properties of RAC**

Due to the complexity of RA, the factors that may affect the properties of RAC have been studied in many literatures.

#### ***Mix proportions***

As expected, the mix proportions, such as water content (W), C, W/C, total aggregate-cement ratio (A/C), fine aggregate percentage ( $S_p$ ), are main factors affecting the properties of concrete. These factors will also undoubtedly

influence the properties of RAC, and in the study of Kou (2006), the influence of these factors on the fresh properties of RAC was analyzed in detail.

### ***Replacement ratio of NA by RA***

Many researchers (Topcu 1997; Limbachiya et al. 2000; Kou 2006; Guan 2011; Kotrayothar 2012) have studied the influence of replacement ratio of NA by RA ( $r$ ) on the mechanical properties of RAC, and most of the findings indicated that the properties of RAC, especially the durability would become poorer gradually with the increase in replacement ratio. It is however believed that there is no influence on the strength of RAC when using RA to substitute 20-30% of NA (Dhir et al. 1999; Limbachiya et al. 2000; Limbachiya 2004), but the properties of RAC will get poorer gradually with more RA replacement adopted. Levy and Helene indicated that the durability of RAC produced with 20% of NA replaced by RA, from old concrete or masonries, could be comparable and even better than those of NAC.

Significant variations could be noticed on the mechanical properties of RAC made with different RA replacement through a comparative summary of some previous studies (Tam et al. 2007), as shown in Table 2-2.

**Table 2-2 - A summary of previous studies on properties of RAC (Tam et al. 2007)**

Source(s)	Replacement ratio	Compressive strength <sup>a</sup>	Flexural strength <sup>a</sup>	Modulus of elasticity <sup>a</sup>
Acker (1998)	100% replacement of coarse recycled aggregate (CRA)	17.2% lower	20% lower	23% lower
Ahmed and Struble (1995)	100% replacement of CRA	33% lower	16% lower (at 14 days)	
Bretschneider (2004)	100% replacement of CRA 75% replacement of CRA 50% replacement of CRA		8.1% lower	11.9% lower 4.0% lower 5.8% lower
Frondistou-Yannas (1977)	100% replacement of CRA	4–14% lower	8.1% lower	40% lower
Grubl et al. (2004)	100% replacement of CRA 75% replacement of CRA 50% replacement of CRA 25% replacement of CRA			28.3% lower 21.9% lower 23.3% lower 13.6% lower
Hansen and Marga (1988)	100% replacement of CRA	30% lower		
Ikeda et al. (1988)	100% replacement of CRA	15–40% lower		30–50% lower
Kakizaki et al. (1988)	100% replacement of CRA and fine recycled aggregate (FRA)	32% lower		40% lower
Masood et al. (2001)	10% replacement of FRA 20% replacement of FRA 30% replacement of FRA	20% lower 22.6% lower 25.5% lower	4.2% lower 7.3% lower 10.4% lower	32.4% lower 22.7% lower 20.2% lower
Nishibayashi and Yamura (1988)	100% replacement of CRA	15–30% lower		15% lower
Roos (2003)	100% replacement of CRA	34% lower		36.4% lower
Teranishi et al. (1998)	50% replacement of CRA	57.8% lower		30.5% lower
Topcu (1997)	30% replacement of CRA <sup>b</sup> 50% replacement of CRA <sup>b</sup> 70% replacement of CRA <sup>b</sup> 100% replacement of CRA <sup>b</sup>	31.8% lower 45.5% lower 54.5% lower 86.4% lower		

<sup>a</sup> Tests are conducted in the curing of 28 days.

<sup>b</sup> The quality of these recycled aggregates is poor, with water absorption of 7% in 30 min.

### *Characteristics of aggregate*

Considering that RAs are generally derived from different practical sources, the properties of RAs may vary greatly, and the properties of RAC made with such RAs will be affected accordingly.

#### (1) Residual mortar

The residual cement mortar in RA render it different from NA, and is also

considered as the main cause of poorer properties of RA compared with those of NA (Otsuki et al. 2003; Etxeberria et al. 2007a; Gonçalves and de Brito 2010; Deshpande et al. 2011). Some other studies (Otsuki et al. 2003; Oikonomou 2005; Deshpande et al. 2011) also reported that the quality and amount of residual cement mortar attached to RAs varied significantly different sources of the RAs used. The great difference would affect the properties of new concrete prepared with such aggregates.

Huge efforts have been made to study the influence of the attached cement mortar on the properties of RA, including methods to measure the amount of  $M_C$ , and the ways to remove the mortar, de Juan and Gutiérrez (2009) indicated that the  $M_C$  was inversely proportional to the size of the RA, and the larger amount of attached mortar would lead to lower density, but higher values of  $W_a$ , LAAV and sulphate contents.

## (2) Processing procedure of RA

Through comparing the long-term properties of concrete made with NA and three sources of RAs, Kou and Poon (2008) found that although the compressive strength of RAC, irrespective of the source of RA, were all lower than that of the

corresponding NAC, the rate of increase in the strength with curing age were different for RAC made with RAs from different sources. Among all the concrete, RAC made with RA crushed from old concrete by hammer manually had the biggest increase in compressive strength after five years' curing relative to other RAs which were crushed using mechanical facilities in different recycling plants. This is mainly due to the presence of more porous old mortar in RA crushed by hammer, which could enhance the cement-aggregate bonding, including the formation of new cement hydrates that would penetrate into the RA. Florea and Brouwers (2013) adopted three crushing methods to process the laboratory prepared concrete, they concluded that crushing method played a significant role in the quality of the produced RA, and an optimized method could be used to produce RA with better quality.

### (3) Type of the virgin aggregate

For the properties of RA used for the production of RAC, the virgin aggregate type originally contained in the RA is very important. This is mainly because the differences in the composition, particle shape and surface texture of different NAs will cause their properties vary largely, which may then affect the properties of the produced RA and RAC. Zega et al. (2010) pointed out that the virgin

aggregate type sometimes could even play a more important part in affecting the properties of RA than the W/C of the original concrete.

#### (4) Quality of parent concrete

The quality of parent concrete is a key factor in affecting the mechanical properties of RAC. Topcu (1997) found that the  $f_{cu}$  of RAC made with 100% RA could be decreased to only about 14% of that of the NAC. That may be due to the poor quality of RA used in the study, with a 30 min  $W_a$  of about 7%. But RAC made with RA derived from high quality parent concrete and underwent appropriate mechanical crushing processes had better  $f_{cu}$  and  $f_{tc}$  (Nagataki et al. 2004). And it is believed that the  $f_{cu}$  of RAC can be comparable and even higher than that of the original concrete (Ajdukiewicz and Kliszczewicz 2002). Ryu (2002) indicated that the mechanical properties of RAC were mainly determined by the weaker quality between the old and new ITZ.

Poon et al. (2004) pointed out that the strength development of the RAC prepared with RA derived from high performance concrete was faster than that from NAC. They attributed the results to the differences in porosity and pore structure of the two types of RAs, and the possible interactions between the RAs

and the cement paste, since the physical properties and bond strength of RA made from high performance concrete were better than those from normal concrete. Ajdukiewicz and Kliszewicz (2002) compared the properties of RAC made with different replacement ratios, W/C, RAs with different strengths (high, medium or low strength), and RA at different moisture conditions. They concluded that the strength of RAC was about 10-25% lower than that of NAC. They also concluded that the  $f_{cu}$  or  $f_{tc}$  loss of RAC prepared with low strength RA was more significant than that of concrete prepared with high strength RA, and the extent of the reduction was related to many parameters, such as the type of concrete used for producing RA (high, medium or low strength),  $r$ , W/C and the moisture conditions of the RA.

#### (5) Moisture condition of RA

For NAC, the moisture state of the aggregate generally would not affect the properties of concrete produced, since the absorption capacity of NA is usually low. However, considering the extremely high porosity and absorption capacity of RA, the situation is extremely different.

When RA is used in the dry condition, the high absorption capacity may cause it

to absorb much mixing water rapidly and lead to lower workability of the fresh concrete. So many researchers (Hansen 1992; Sagoe-Crentsil et al. 2001; Etxeberria et al.2007a) suggested that the RA should be kept in a pre-wetted or a saturated state prior to use.

However, Kou (2006) argued that the high water content inside the RA particles might result in “bleeding” during casting if the RA is in the SSD state. He pointed out that the  $f_{cu}$  of the produced concrete made with such RA would be reduced, and he further suggested that the use of SSD or over wetted RA in preparing RAC should be avoided.

But Etxeberria et al. (2007a) indicated that wet processing of RA could get concrete with better properties. While Mefteh et al. (2013) examined the fresh and hardened properties of RAC made with RA in different moisture states (dry, pre-wetted and SSD), and they found that the use of RA in the dry condition could produce concrete with the highest strength. Poon et al. (2004) pointed that the optimal moisture condition of RA for concrete production was neither dry nor saturated, but the air dry (as-received) state. This viewpoint was also consistent with the experimental results of Pelufo et al. (2009).

### ***Mixing procedure***

Tam et al. (2005; 2006) indicated that relative to traditional mixing method for NAC, a two-stage mixing approach could fill up the cracks and pores present in the RA through a premixing process, thus making the RAC denser and forming a stronger ITZ around RA. Accordingly, the mechanical properties of the produced RAC could be improved.

### ***Cement type***

As accepted, the strength of concrete is affected significantly by the water binder ratio, the extent of hydration, the curing condition and the curing ages (T). It is the chemical reaction between the hydraulic cement and water-hydration that makes the produced concrete strong and durable. So the cement type ( $T_C$ ) is a key factor that may affect the properties of normal and recycled concrete.

Jankovic et al. (2011) indicated that for concrete made with rapid hardening Portland cement (CEM I), it generally had lower porosity and higher strength when compared with the concrete made with cement of other types. This is mainly due to the higher fineness of CEM I. Mas et al. (2012) also noticed the

great differences in the reduction of the strength of RAC made with recycled mixed aggregate when different types of cement were adopted. Therefore, the cement type used should be also considered when comparing the experimental results of RAC obtained by different researchers.

### ***Masonry content***

In many countries, including China, clay bricks and tiles constitute a large fraction of the construction and building wastes. The presences of these materials make it more difficult to recycle and reuse the wastes. This is mainly because that the  $W_a$  and porosity of masonry materials are generally several times higher than those of the NA and crushed concrete, and may be harmful to the properties of produced concrete.

Khalaf (2006) indicated that the properties of concrete made with crushed clay bricks were affected largely by the quality of the original bricks, and the  $f_{cu}$  of concrete made with crushed bricks of high quality could even exceed that of the concrete made with NA. While another study (Debieb and Kenai, 2008) found that the percentage of entrained air in concrete increased with the increase in the replacement ratio of NA by crushed bricks, and the  $f_{cu}$  of brick aggregate

concrete was about 10-35% lower than that of the corresponding normal concrete. As regards the  $E_c$ , Correia et al. (2006) reported a decrease of about 30-40% for the recycled brick concrete in comparison with that of the corresponding NAC.

A review of literatures made by Paine and Dhir (2010) concluded that the properties of concrete containing recycled bricks, such as compressive, tensile and flexural strength, and elastic modulus, were generally poorer than those of the traditional concrete, since crushed bricks were usually porous and weak. But they also pointed out that the use of crushed bricks in concrete might improve the resistance to the carbonation, alkali-silica reaction and freeze-thaw attack.

### ***Impurities***

Apart from the attached cement mortar, impurities present in the RA, such as glass, asphalt, plastic, wood, gypsum, clay, etc, are also regarded as key components that may have adverse effects on the properties of new concrete (Kesegic et al. 2008; Chen et al. 2003; Poon and Chan 2007; Debieb et al. 2010), especially on the durability. Therefore, most of the specifications governing the use of RAC generally impose a maximum allowable quantity of impurities content ( $\delta$ ) in RA, to ensure the properties of RAC can be comparable with that

of NAC. According to the specification on RA in Hong Kong (Fong et al. 2004), the content of wood and other materials less dense than water in RA should be no more than 0.5 wt. %, while the content of other foreign materials (including metals, plastics, clay lumps, glass, asphalt, etc) in RA should be lower than 1 wt. %.

### ***Problems of the use of RA in new concrete***

With increasing attention paid to the research of RCA, it is generally realized that the reuse of RCA to replace NA for concrete production can save large quantities of natural resources. However, the properties of concrete made with RAs should meet the requirements designed for NAC. So it is necessary to accurately assess the characteristics of RAs from different sources, as predict as the influence of RA quality and its effect on the properties of new concrete.

Unlike NAC, for which various mature and reliable design codes and empirical formula have already been established for facilitating the prediction of the hardened properties as well as the design of the mix proportions, there is still no standard method addressing the mix design procedure for RAC, not to mention reliable and generalized mathematical models for the prediction of its hardened properties.

As a modeling tool, artificial neural networks (ANN) has been widely used in a variety of engineering applications since the mid-1980s, and it has also been demonstrated to have superior capacities in modeling more complex relationships in various engineering applications due to its generalization property. However, currently ANN is mainly used in concrete made only with NA, and is rarely adopted in RAC because the more complex composition of RA, although Topçu and Sarıdemir (2008) conducted a trial on predicting the compressive and tensile strengths of RAC containing silica fume.

This research aims to investigate whether or not ANN can be used to model the properties of concrete made with RAs from different sources.

## **2.4 ARTIFICIAL NEURAL NETWORKS**

### **2.4.1 Introduction of artificial neural networks**

#### *Artificial Intelligence*

With the rapid development of the science and technology, automation and artificial intelligence (AI) have received increasingly wider application in various

fields. As we all know that computers have superior memory capacity, rapider processing power and higher calculation accuracy when compared to human brain. Considering that the strong computing capacity and accuracy of computer in numerical and logical computation, it can expand the ability of the brain greatly, thus help much work in the daily lives of human beings get more effective solution. However, computer itself cannot think, it is the logical rules preset by human that make it run orderly, and what the computer can do is to perform the simple or complex programs wrote by human. At present, it is still difficult for the computer to deal with some problems that need it study independently.

The highest level of intelligence is biological intelligence (BI), among which the most intelligent is definitely human beings. There are more than 10 billion neuron cells in human brain, which can record about 86 million messages every day. The transmission of such cells is mainly relying on the electrical pulses and chemical kinetics, and information can be passed from one cell to another one through releasing neurotransmitter. Different neurotransmitters carry different signals: some are excitability, while some are inhibitory. The excited signal can lead the muscles cells shrinkage or help the glandular cells increase secretion

through prompting the discharge of neuron fibers; while the suppressed signal may prevent the discharge of neuron fibers, thereby inhibiting the contraction of muscle and lead the muscle relax.

It requires only about 0.001-0.003 seconds for the neurotransmitters to transmit one message. Therefore, human brain, a complex, nonlinear and parallel information processing system, can be regarded as an intelligent computer.

Though the computing speed and accuracy of brain cannot be compared with the computer, human brain can be able to run with psychological processes, such as thinking and judging perceptually. Thanks to such abilities of thinking and logical reasoning, human beings are able to survive, adapt and change the world.

It may be very interesting to apply the ability of brain like logical reasoning to the computer, the intelligent computer, namely AI can then help people better know and change the world. But how to make the computer intelligence is a major problem.

AI was first studied as an independent field at a conference in Dartmouth College in 1956 (Crevier 1993). It aims to study how to develop or manufacture artificial intelligent machines or systems that can be capable of simulating the intelligence

of human. The object of the field mainly includes robotics, voice recognition, image recognition, natural language processing and expert systems.

The study of AI was mainly focused on symbol processing and logical reasoning in the early stage, namely symbolism intelligence (SI), but such methods became increasingly powerless when dealing with some complex nonlinear and uncertain issues with the development of science and technology. Then the computation intelligence (CI) was developed, which can be able to help the computers more intelligent and more flexibility in the service of humanity with compared to SI. This is contributed to the CI can be capable of learning from data, without the need to establish a precise mathematical model for the problems to be solved, which is also the most important feature of the CI.

With the depth theoretical and technical study of AI, many achievements have gradually entered in to peoples' daily life. Industrial automation is closely related to the AI, since the study and application of AI in control industry can not only enrich the theory and technology, thus promote the development of the whole field if AI, but also further expand the application of AI. So this study is very important and valuable.

### *Artificial neural networks*

ANN is one of the main methods of CI, it is a nonlinear adaptive information processing system that is consisted of a large number of interconnected processing units. As mentioned in the previous section, a human brain contains over 10 billion neurons (Pelvig et al. 2008); each neuron is connected to several thousand other neurons through synapses, forming a complex biological neural network (BNN). Accordingly, the ANN aims to process information by simulating the method of BNN in processing information and data.

#### (1) The definition of ANN

So far, there is no formal definition of ANN. In the opinion of Hecht-Nielsen (1989), a neural network is a parallel, distributed information processing structure consisting of processing elements (which can possess a local memory and can carry out localized information processing operations) interconnected together with unidirectional signal channels called connections. While for Kohohen (1995; 1997), ANN is adaptive to a wide range of simple modules in parallel interconnection network, which can simulate the organization of biological nervous systems made of real world objects, interactive response.

ANN is a simplified model constructed from the abstraction of brain neural networks by using the methods of mathematics and physics and the point of signal processing. Simply speaking, ANN is an information processing system that aimed to model the structure and function of the brain.

## (2) The development of ANN

From the 1940s, with the breakthrough progress in the research of the neuroanatomical, neurobiology and neuronal electrophysiological processes, people has grasped increasingly more knowledge of the internal structure, composition and the basic unit of the brain, more and more studies have been conducted to the use of ANN. So far, the study of ANN can be divided into three stages.

### Early stage

In 1943, the computational model for neuron networks, first proposed by McCulloch and Pitts (1943) and was based on mathematics and algorithms, is still in use today and has a direct impact on the progress of this field. Therefore, the two researchers can be regarded as pioneers in the study of ANN, and some

of their findings are still used as the basis of ANN until now.

In 1948, John von Neumann, a founding figure in computer science, proposed a regenerated automata network structure consisted of simple neurons through comparing the difference between the brain structure and stored program computer. He is also regarded as one of the pioneers in ANN research.

However, the ANN research was limited to theoretical investigation till the creation of perceptron (Rosenblatt 1958), an algorithm for pattern recognition based on a two-layer learning computer network. Since then, a growing number of studies have tried to apply the ANN to many applications, such as character recognition, voice recognition and sonar signal recognition. The development of the adaptive linear neuron in 1960 (Widrow and Hoff 1960), also helped to form the foundation of many nonlinear multilayer adaptive networks proposed in later studies.

#### Recession stage

However, many researches mistakenly thought that the digital computer was the solution to all the problems like AI, pattern recognition and expert system. Much

lesser effort was given to ANN research gradually. Besides, the publication of machine learning research by Minsky and Papert (1969) was also a reason that made the ANN research stagnated, since they indicated two serious problems with the ANN. One was that a single-layer ANN was not able to handle the exclusive-or circuit. The other one was that the computers at that time were not fast enough to process the large ANN models.

#### Revival stage

The recession stage of ANN lasted until the early 1980s when the development of digital computers was encountering difficulties in many application areas. Meanwhile, the breakthrough in the field of ANN caused another boom for its research. In 1986, the development of a back-propagation (BP) algorithm (Rumelhart et al. 1986) enabled enormous potentials for application of neural networks. The BP algorithm is able to overcome the limitations of perceptron as it can also be used in nonlinear cases. The research on ANN has since entered into the revival stage.

#### (3) The working principle of ANN

ANN is an information processing system that aims to model the structure and

function of the brain. So it is necessary to introduce the structure and features of the brain before introducing the working principle of ANN.

### Biological neuron

A nerve cell, namely neuron was first defined by Wilhelm Waldeyer in 1888 (Cremer and Cremer 1998), and three years later, he created the neuron theory.

In his theory as seen in Figure 2-4, a neuron is a basic unit of the nervous system, and generally constituted by soma and processes, which can be divided into dendrite and axon. The dendrite can accept an impulse and transmit it to the soma; while the axon can pass the impulse to the terminals, which are the branches of the axon. A neuron generally has only one axon and one or more dendrite. So it can be said that a typical feature of a neuron to process signals is it has many inputs and a single output. The soma acts as the role of information processing, when the pulse transmitted to the presynaptic neuron through the axon reaches certain intensity, exceeding the threshold potential, the presynaptic neuron will release a chemical called neurotransmitter to the gap junctions of a synapse.

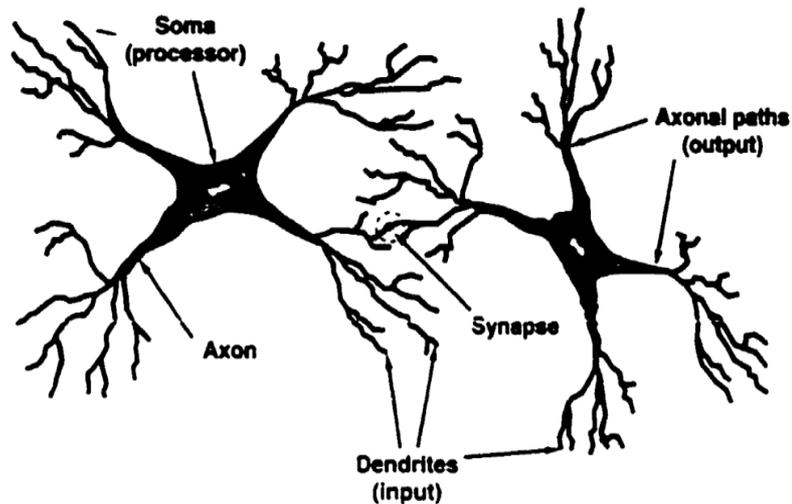


Figure 2-4 - A simple biological neuron

In a nervous system, each neuron is interconnected to some other neurons, and signals are transmitted from the axon of one neuron to the soma and dendrites of other neurons. A synapse is just the junction of the signal transmission from one neuron to other neurons. Signals of synapse can be either excitatory or inhibitory. The excitatory signal can lead the muscles cells shrinkage or help the glandular cells increase secretion through prompting the discharge of neuron fibers; while the suppressed signal may prevent the discharge of neuron fibers, thereby inhibiting the contraction of muscle and lead the muscle to relax.

A biological neural network is formed by the interconnected neurons through synapses, it receives a variety of information from both inside and outside the body by the sensory organs and nerves, and passes them to the central nervous

system. After analysis and synthesis of the information, the control information is sent through motor nervous to achieve the contact of the body with the internal and external environment, thus coordinate the various functions of the whole body. The structure and function of each neuron are all simple, but the behavior of the biological neuron networks constituted by a large number of these neurons is much more complicated.

#### Artificial neuron

In an ANN, the way for the biological neurons to transmit information is simulated by artificial neurons as shown in Figure 2-5. Variables  $(x_1, x_2, \dots, x_n)$ , represent the input signals, and are given the corresponding weights  $(w_1, w_2, \dots, w_n)$ -acting as the size of synapses-at the nodes (dendrites), respectively. Then the modified signals (variables are multiplied by the corresponding weights) are linked to the specified Y node (soma). Once the sum of these modified signals exceeds a threshold value  $(\theta)$ , the artificial neuron will generate a signal of its own. The value at the Y node can be calculated through the activation function as Eq. (2-1):

$$Y=f(\cdot)=f[\sum_{i=1}^n(x_i w_i) - \theta] \quad (2-1)$$

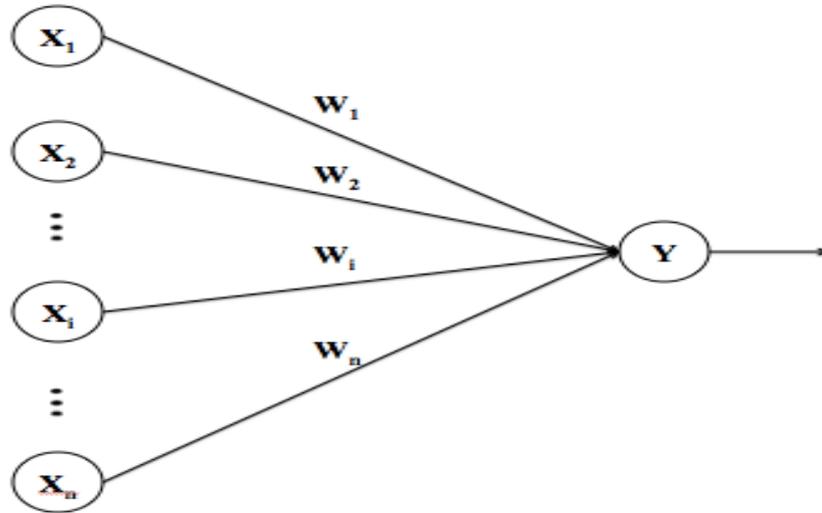


Figure 2-5 - An artificial neuron

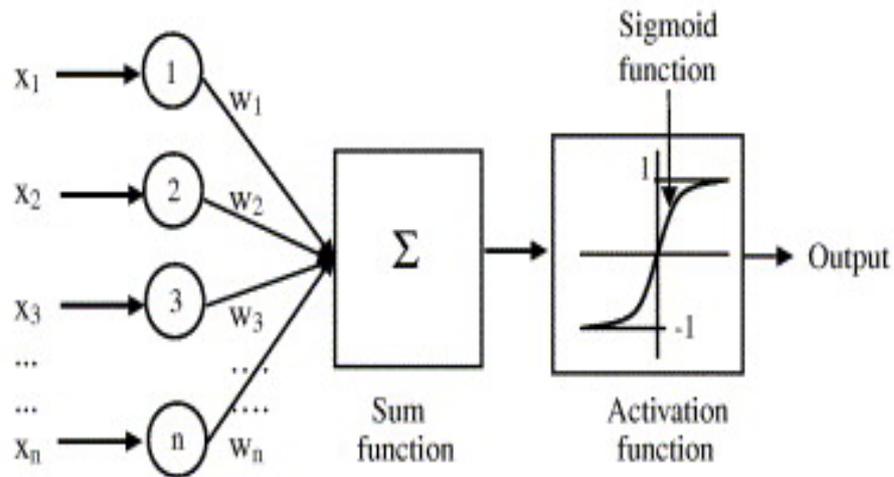


Figure 2-6 - A simple neuron model

The activation function plays an important role in the process of transmitting information from the input variables to the Y node: It is used to control the activating function of the inputs to the output and conduct function convention to both the inputs and the output; besides, it can transform the inputs, may be in unspecified ranges, into the output in a specified range.

## Neural networks

Just like the BNN, an ANN as shown in Figure 2-6 (Anderson 1983; Akkurt et al. 2003) is consisted of a number of interconnected groups of artificial neurons, each of which is fully connected to the other through connection weights and receives an input signal from the neurons linked to it. These weights, present the effect of each input parameter in the previous layer on the process element, respectively, can be adjusted to produce an output needed. Information is transmitted to the output layer from the input layer in one direction, along with which learning process is conducted to minimize the deviation between the actual values and output values. In most cases an ANN is an adaptive system that can change its model according to relevant information that flows through the network during the learning phase. An ANN can be used to model nearly any complex relationships between the inputs and the outputs data.

Generally, ANN can be said to be superior to other traditional computational methods (Arslan and Ince 1996). The superiority of ANN will show only when the traditional methods are poor or not able to solve the problems, and such superiority is more obvious when the problem's nature is not clear or the

problem cannot be expressed by using any mathematics models, such as in failure analysis and prediction. The other advantage of ANN is that it has greater flexibility and adaptability when there is a large amount of original data for the problem but rules or formulas are no longer applicable.

#### **2.4.2 Back-propagation Neural Networks**

Among various ANN architectures, the back-propagation neural networks (BPNN) is one of the simple and most applicable networks being used in modeling the performances of concrete, mainly due to it can adjust the weights of each layer based on the errors present at the network output. A typical structure of BPNN model consists of an input layer, one or more hidden layers and an output layer, and each layer consists of numerous neurons.

The neural network based modeling process involves five main aspects: (1) data acquisition, analysis and problem representation; (2) architecture determination; (3) learning process determination; (4) training of the networks; and (5) testing of the trained network for generalization evaluation (Öztaş et al. 2006). More details regarding the construction of ANN can be found in the quoted references (Hornik et al. 1989; 1990; Topcu and Saridemir 2008; Trtnik et al. 2009).

The training set of BPNN contains two stages, one is feed-forward stage and the other is back-propagation stage. In the former stage, the input layer neurons pass the input mode onto the hidden layer. Each of the hidden layer neurons computes a weighted sum of its input, and passes the sum through its activation function and presents the activation value to the output layer. Following the computation of a weighted sum of each neuron in the output layer, the sum is passed through its activation function, resulting in one output value for the network. Usually, a sigmoidal function ( $f(.)$ ) is used. The output is calculated according to Eq.(2-2):

$$f_j = \frac{1}{1 + \exp(-\sum w_{ji}o_i + b)} \quad (2-2)$$

where  $w_{ji}$  is the connection weight from the neuron  $i$  in the lower layer to neuron  $j$  in the upper layer and an initially small random value,  $o_i$  is the output of the neuron  $i$ , and  $b$  is the bias value.

The error of network is passed backwards from the output layer to the input layer, and the weights are adjusted based on some learning strategies so as to reduce the network error to an acceptable level. In this study, the error arose during the training and testing in ANN and fuzzy logic models can be expressed as a

root-mean-squared error (RMS) and is calculated using Eq.(2-3) according to Pala et al (2007) and Oztaş et al (2006), the absolute fraction of variance ( $R^2$ ) and mean absolute percentage error (MAPE) are computed by Eq. (2-4) and Eq. (2-5), respectively.

$$\mathbf{RMSE} = \sqrt{\left(\frac{1}{P}\right) \times \sum_j |t_j - o_j|^2} \quad (2-3)$$

$$\mathbf{R}^2 = 1 - \left(\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2}\right) \quad (2-4)$$

$$\mathbf{MAPE} = \left(\frac{o - t}{o}\right) \times 100 \quad (2-5)$$

where  $t$  and  $o$  are the predicted and actual output of the network, respectively, and  $p$  is the total number of training and testing patterns.

### 2.4.3 The construction of ANN model

#### *The selection and process of sample data (normalization)*

First of all, enough sample data of good representation and accuracy is the primary requirement for establishing a model using BPNN. These sample data should be randomly divided into three parts, namely training sample, validation sample and testing sample and the latter two parts are at least 20% of the total sample. This is to avoid the occurrence of over-fitting in the training process as

well as to evaluate the performance and generalization abilities of the constructed model. In addition, the balance among the sample modes should be also considered for division of the sample data.

The determination of the input and output variables is also very important. The selection of the input variables is generally based on the professional knowledge of the researcher by analyzing the factors that may influence the output parameter. In the case there are sufficient sample data, the more parameters selected in the input layer, the higher accuracy of the model may achieve. However, the choice of excessive input variables without the support of enough sample data may lead to poor training and instability of the network. So it is better to conduct sensitivity analyses after the network training to reduce and optimize the input variables. For each ANN, there may be one or more output variables based on the needs of the researcher. But in general, under the condition of using the same amount of sample data, using several ANN models and each with only one output may be more convenient and is able to produce better predictions compared to a model with several outputs.

It is necessary to preprocess the original sample data of both the input and output

variables. As varieties of sigmoid functions are generally adopted as the activation function in the hidden layer of BPNN, the input and output values are required to be in the range of 0-1 to enhance the model's training speed and sensitivity, as well as to avoid the saturated zone of the sigmoid functions. Therefore, the sample data of BPNN should be preprocessed. Researchers can preprocess either the different sets of variables separately, or all the variables using a unified formulae based on the need. There are a variety of methods for normalization. No matter which method is used, the outputs of the model after training of the preprocessed data should be unnormalized to get back the actual values. Besides, it is better to normalize the sample data to a narrower range, such as 0.1-0.9 and 0.2-0.8, to ensure the generalization ability of the established model.

### ***The selection of number of hidden layer***

In general, a three-layer network with one hidden layer should be the optimum when constructing a BPNN model. More hidden layers ( $\geq 2$ ) may reduce the error, thus improve the accuracy of the network, but it will also make the network more complex and thereby increase its training time, besides, it may make the network more prone to over-fitting. While a network without a hidden

layer is equivalent to regression analysis, so there is no need to discuss such kind of network for constructing BPNN with high accuracy. It seems that the lower error can be obtained more easily by adding the nodes of the hidden layer than increasing the number of hidden layer, and many studies have pointed out that the predicted results of BPNN with one hidden layer and appropriate hidden layer neurons can approach the actual values with the best accuracy.

#### ***The selection of nodes number in hidden layer***

In addition to the number of hidden layer, the selection of number of nodes in the hidden layer is also very important. The number of hidden layer nodes is generally believed as the main reason that leads to the occurrence of over-fitting in the training process. However, there are still no established methods for researchers to determine the best node number. So researchers are generally required to adjust the nodes number, by a trial and error method to determine the best value. The process is quite time-consuming.

As mentioned above, the use of an inappropriate node number in the hidden layer may lead the network over-fit. To avoid such phenomenon, as well as to provide the network with sufficient high accuracy and generalization ability, it is better to

select the as few as possible node number to start with given the condition of the network is able to meet the required accuracy.

### ***The determination of the parameters for network training***

#### (1) Weight and threshold

Weight and threshold, are connections between the input and output neurons, and play the role of synapse in a biological neural network. BP algorithm involves two parts: forward propagation of the input signal and back propagation of the error: for each propagation, the network will calculate an output based on the input data, and compare it with the actual output. The error between which will then be passed in the opposite direction. During the process, the weight and threshold are adjusted and corrected to minimize the error of the network. The modified weight and threshold will be then applied to the next propagation till the network reaches the expected error or the maximum training epochs. The initial weight and threshold are generally generated by the system.

#### (2) Learning rate

Learning rate can determine the training speed of the network through modifying the weights and thresholds during each propagation. So an appropriate learning

rate is very important to establish a good model. A too big value may cause network instability, while it may take too long and be difficult to convergence if the learning rate is too small. Generally, a smaller learning rate (0.01-0.3) will be a priority to ensure the stability of training.

### (3) Momentum coefficient

The addition of momentum coefficient in BP algorithm can avoid the training of the network being trapped into a local minimum, and its value is generally set in the range of 0-1.

#### **2.4.4 Sensitivity analysis**

Sensitivity analysis, an uncertainty analysis technique in relation to quantitative analysis, is a study how sensitive of the prediction results of the model to the change of selected input parameters. It also determines the significance of these uncertainty factors on the results (Khatri and Sirivivatnanon 2004; El-Dash and Ramadan 2006; Zhang et al. 2006). So it is necessary to apply the sensitivity analysis to the constructed ANN model to further study the influence of each input variable on the output. By conducting sensitivity analysis, Jain et al. (2008) determined the effect of the constituents of concrete mixes to the desired

workability.

Many methods have 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 parameters. A Taylor series was used to determine the importance of each parameter to the chloride diffusion coefficient (Sun et al. 2011). Lu et al. (2001) analyzed the sensitivity of BPNN based on Monte Carlo simulation, and successfully applied the results to some applications. Nyarko et al. (2011) identified the most important parameters in affecting the damage level of a structure through comparing the networks errors of all possible combinations of input variables.

#### **2.4.5 Application of neural networks in natural aggregate concrete**

Civil engineering applications of ANN have recently been successfully used in many areas (Adeli 2001): (1) structural engineering (Vanluchene and Roufai 1990; Chen et al. 1995); (2) construction engineering (Karim and Adeli 1999; Adeli and Saleh 1999); (3) Environmental and water resources engineering (Guo 2001); (4) Traffic engineering (Saito and Fan 2000); (5) Highway engineering (Owusu-Ababio 1998); (6) Geotechnical engineering (Juang et al. 1999; Shahin et

al. 2008).

While for concrete, the current application of ANN is mainly performed to model the fresh or hardened properties (Lee 2003; Yeh 2006; Ahmet et al. 2006; David et al. 2013) and mix design (Yeh 1999; Oh et al. 1999; Wang and Ni 1999; Garg 2003; Kim et al. 2013).

### ***Strength prediction***

Over the last two decades, ANN has been used by many investigators for predicting the mechanical properties of concrete for its high accuracy and non-destructive procedure. And the application of neural networks has been widely documented for normal concrete (Ozturan et al. 2008; Yousif and Abdullah 2009), high performance concrete (Kasperkiewicz et al. 1995; Yeh 1998), structural lightweight concrete (Mirza and El-Bisy 2006; Alshihri et al. 2009), self-compacting concrete (Nehdi et al. 2001; Suryadi et al. 2011; Uysal and Tanyildizi 2012) and RAC (Topcu and Sarıdemir 2008; Chan et al. 2012). Lee (2003) proposed some ANN architectures to model the  $f_{cu}$  of concrete. Through collecting sample data from different published literatures, Noorzai et al. (2007) developed ANN models by using these data that were capable of

predicting the 28d  $f_{cu}$  of concrete accurately.

Some researchers (Alilou and Teshnehlab 2010; Hasan and Kabir 2011) adopted the ANN approach to estimate the 28d  $f_{cu}$  of concrete based on the strength tested at earlier ages. Bilgehan and Turgut (2010) evaluated the  $f_{cu}$  of concrete cores by using ANN based on the ultrasonic pulse velocity and density results of many cores taken from different concrete structures with different ages and unknown mix proportions. Atici (2011) developed an ANN approach to estimate the  $f_{cu}$  of concrete that contains various amounts of mineral admixtures at different curing times, and compared the predicted results with those modeled by multiple regression analysis. Based on the results, the author indicated that the ANN method was more suitable for use, though the method of multiple regression analysis had many advantages. Sobhani et al. (2010) developed some models to estimate the 28d  $f_{cu}$  of no-slump concrete by adopting three approaches: regression analysis, neural networks and adaptive network-based fuzzy inference systems. They found that the latter two AI-based approaches performed better than the traditional regression models. Dias and Pooliyadda (2001) successfully developed BPNN models for predicting the strength and slump of concrete with admixtures, and also examined the effect of the input factors on the strength

through sensitivity analysis. Most of the studies related to the strength prediction by ANN are focused on the  $f_{cu}$ , only a few literatures discussed the use of ANN for modeling the  $f_{tc}$  (Topcu and Sarıdemir 2008), flexural strength (David and Chioma 2013) and shear strength (Young II et al. 2008).

### ***Slump and density***

There are also many studies discussing the application of neural networks in estimating the slump or/and density of concrete. Chine et al. (2010) developed an BPNN model for predicting the slump of concrete by using the concrete mix proportions as inputs, and the predicted accuracy of networks was proved much better than that of traditional multiple regression analysis. Yeh (2007) and Mazloom (2013) also successfully modeled the slump flow of concrete by using neural networks. By selecting five input variables including water-cementitious material ratio,  $T_C$ ,  $C$ , and the amounts of silica fume and superplasticizer, Rasa et al. (2009) successfully constructed an ANN model for estimating the 28d density and  $f_{cu}$  of concrete with high accuracy.

### ***Elastic modulus***

$E_c$  is a very important mechanical parameter, reflecting the ability of the concrete

to deform elastically. However, the testing procedures for determining the  $E_c$  of concrete are rather complex and time consuming, making it difficult to obtain the value in engineering applications (Demir 2008). Some studies (Hanet al.2003; Liu 2007; Demir 2008) on the use of ANN for predicting the  $E_c$  of concrete have proved that ANN performed better than some other methods like traditional regression analysis.

### ***Other properties***

Parichatprecha and Nimityongskul (2009) constructed a reliable and accurate ANN model to predict the chloride ions (Cl<sup>-</sup>) permeability of concrete that performed better than regression analysis. Bal and Buyle-Bodin (2013) developed a multilayer ANN model that provided good predictions on the drying shrinkage of concrete. Another study conducted by Karthikeyan et al. (2008) used neural networks in high performance concrete could not only predict the shrinkage strain effectively, but also capable of producing similar creep strain values as the experimental results. Lu and Liu (2009) developed two ANN models for estimating the carbonation depth of concrete, and found that both models had high generalization abilities. Zhong et al. (2004) indicated that ANN could also be applied to predict the service life of concrete under sulphate

erosion.

#### **2.4.6 Application of neural networks in recycled aggregate concrete**

However, currently ANN are mainly used in concrete made only with NA, and is rarely adopted in the concrete containing RA due to the complex composition, although Topcu and Saridemir (2008) made a trial on predicting the  $f_{cu}$  and  $f_{tc}$  values of RAC containing silica fume. Han and Zhang (2008) used ANN with the Levenberg-Marquart algorithm to predict the 28-day  $f_{cu}$  of RAC. Li and Yang (2009) used the ANN method to design the mix proportion of RAC. Although the ANN models constructed by the above researchers generally performed satisfactory using data from their own studies, whether or not these models are suitable to forecast data from other sources have not been proved.

### **2.5 SUMMARY**

- Compared with NA, RA derived from concrete debris contains large amounts of old attached mortar. The attached old cement mortar and the original aggregate used are usually the key components affecting the properties of the RA. RAs 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 seriously 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 RA may vary greatly.

- Concrete made with RA generally performs poorer than the corresponding NAC, and the unstable performance of RA obtained from variable sources and produced by different crushing methods will definitely cause fluctuations in the properties of RAC. The properties of RAC made with high quality RA can be comparable with 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 RA are rarely noticed in concrete made with the “virgin” material - NA. This may be the reason why RA is not commonly used in structural concrete, but mostly only as road sub-base or backfilling materials.
- It is necessary to accurately assess the characteristics of RA from different sources, as well as the influence of RA 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 method addressing the mix design procedure for RAC, not to mention reliable and generalized models for the prediction of its hardened properties.

- The use of ANN in the area of concrete technology has been reviewed, and it has been demonstrated by many literature that ANN is capable of providing good predictions of hardened properties of NAC.
- Few studies have been performed on using ANN in the area of RAC.

A large number of studies have been carried out to explore ways to improve the properties of RA, thus to enhance the properties of RAC made with the improved RA. The improvement of the quality of RA is important; but it is also necessary to develop an effective method that is capable of predicting the properties of RAC made with RAs derived from different sources. To achieve the research objectives, there are still outstanding problems to be resolved based on the review results of the literatures :

- There is significant discreteness on the test results reported in the literatures on the properties of RAs and that of the corresponding RAC, so it is necessary to verify the results by experimental investigation the nature of different types of RAs, as well as their influence on the properties of the new concrete.
- Due to the complex nature of RA, there are many more factors that may affect the properties of RAC compared with those of NAC. In such cases, traditional regression analysis may be not suitable for use in modeling the properties of RAC. The use of ANN in RAC has been rarely reported, and the few existing literatures on the use of ANN in RAC and NAC have barely taken the full benefits of ANN. Therefore, there is a need to optimize the ANN method.
- As there are too many factors that may affect the properties of concrete made with different sources of RAs, it is necessary to examine the relative importance of these factors in order to facilitate the use of RAs in new concrete production.



### **3.1 INTRODUCTION**

The above diagram (Figure 3-1) summarizes the work carried out in this PhD study to achieve the desired objectives.

As shown in Figure 3-1, the study program mainly contains two parts: experimental program and the ANN application. In the experimental program, a series of concrete mixes are prepared in the laboratory to investigate the effects of different types of RAs on the properties of RAC, and also to obtain the  $f_{cu}$  and  $E_c$  values at different curing ages. Then the feasibilities of some established relationships in modeling the above properties are evaluated. For the part of ANN application, the obtained experimental results tested at 28 days are firstly used as cases to investigate the general applicability of the constructed ANN models. These models are also aimed to study the influence of each aggregate characteristic examined on the  $f_{cu}$  and  $E_c$  of RAC, respectively.

### **3.2 EXPERIMENTAL PROGRAM**

3 groups with a total of 46 RAC concrete mixes are prepared to examine the effect of different RAs on the properties of RAC. The RAs used are categorized into 3 groups:

- Group1: RAs derived from laboratory prepared concrete cubes with different compressive strength (35-85 MPa);
- Group 2: RAs derived from 3 different sources and crushed by different methods;
- Group 3: RAs contain different amounts of added masonry (clay bricks or tiles).

The performance of materials, mix proportions of concrete, and test methods of the concrete properties are mainly introduced in this chapter.

For the first Group, 5 series of natural aggregate concrete mixtures are prepared with different water to cement ratios to obtain concrete of different strength. The hardened concrete specimens of each series are then crushed by hammer manually to produce RAs of different specified particle sizes after 90 days' water curing. The crushed RAs from each series, together with NA, are used to prepare high strength concrete with a same W/C of 0.35, and appropriate amounts of superplasticizer are added to achieve a similar slump value of 120-150 mm for all mixtures. The aim of this experimental programme is to examine the performance difference of different types of RA and concrete mixtures made by these aggregates.

While for the second Group, four series of concrete mixtures are prepared using NA and three types of RAs. The RAs are obtained by different crushing methods and derived from different batches. In each series, four concrete mixes with different 28d target cube strength between 30 MPa and 80 MPa are prepared, and the corresponding water to cement ratios range from 0.68 to 0.34. For each concrete mix, a control concrete (NC) is prepared with 100% NA, while RC1, RC2 and RC3 are made with 100% RA1, RA2 and RA3, respectively. For concrete made with different types of aggregates, appropriate amounts of superplasticizer are used to achieve a similar slump value of 70-90 mm for Series I to Series III and 120-150 mm for Series IV. The aim of this experimental programme is to examine the performance difference of different sources of RA and concrete mixtures made by these aggregates. Besides, the influence of different sources of RA on the properties of RAC with different designed strength is also investigated.

With respect to the third Group, the performance of RAC made with coarse aggregates containing different masonry contents is studied. Firstly, the performance of RAC made with NA replaced by 0, 50 and 100% RA is examined. Furthermore, crushed bricks and tiles are respectively employed as

masonry and added to the RA. The volume replacement ratio of RA by crushed bricks and tiles are 0, 5, 10, 15% and 0, 5%, 10%, respectively.

### 3.2.1 Materials

#### *Cement*

ASTM Type I ordinary Portland cement from China Cement (H.K) Co. Ltd., with a density and specific surface area of 3.15 g/cm<sup>3</sup> and 3519.5 cm<sup>2</sup>/g, is used.

The chemical compositions of the cement are shown in Table 3-1.

**Table 3-1 - Chemical compositions of cement**

Materials	Composition w/%						
	<i>LOI</i>	<i>SiO<sub>2</sub></i>	<i>Fe<sub>2</sub>O<sub>3</sub></i>	<i>Al<sub>2</sub>O<sub>3</sub></i>	<i>CaO</i>	<i>MgO</i>	<i>SO<sub>3</sub></i>
Cement	2.97	19.61	3.32	7.33	63.15	2.54	2.13

#### *Fine aggregate*

The very high water absorption values of recycled fine aggregates would render them not suitable for producing new concrete (Etxeberria et al. 2007a), since it would lead to excessive drying shrinkage. So this study only discusses the use of recycled coarse aggregates in new concrete. Natural river sand and crushed stone fines (CSF) are adopted as natural fine aggregate for concrete production.



**Figure 3-2 - Laboratory mini-crusher**

### ***Natural coarse aggregate***

Two sources of crushed granite are used as natural coarse aggregate for concrete production. There are large differences between the properties of the two aggregates, which will be discussed in the following section.

### ***Recycled coarse aggregate***

Nine types of recycled concrete aggregates and two types of masonry aggregates are adopted as recycled coarse aggregate. Their sources and preparation methods are described as follows:

- RA1-RA5: RA1-RA5 (10-20 mm and 5-10 mm) are obtained from crushing (manually by hammer) old concrete cubes (150 mm) that have been previously

prepared in our laboratory. The strength of the old concrete cubes increased gradually from RA1 to RA5.

- RA6: RA6 (10-20 mm) is collected from a construction waste recycling plant in Hong Kong which processes both crushed concrete and excavated rock from construction and demolition activities. The plant utilizes a range of crushing and sieving processes to produce the RA; RA6 (5-10 mm) is obtained from further crushing the RA6 (10-20 mm) by a laboratory mini crusher;
- RA7: RA7 (10-20 mm) is also collected from the same recycling plant, but the source of the construction waste is different, so the composition and properties of RA6 (10-20 mm) and RA7 (10-20 mm) are not the same; RA7 (5-10 mm) is obtained by crushing concrete lump from a demolition site, which was originally larger than 200 mm in size, manually (using a hammer) and crushed to 50-80 mm and then by a laboratory mini-crusher, as shown in Figure 3-1.
- RA8: RA8 (10-20 mm and 5-10 mm) is obtained from crushing (manually and by a laboratory mini-crusher) old concrete prisms that had been previously prepared in our laboratory with an original 28<sup>th</sup> day compressive strength of about 45 MPa.
- RA9: RA9 (10-20 mm and 5-10 mm) are both collected from the same recycling plant.

- Bricks and tiles: bricks (10-20 mm and 5-10 mm) and tiles (5-10 mm) are obtained by crushing (manually by hammer) brick and tile specimens purchased from the market. They are used as the added masonry of NA or RA.

**Table 3-2 - Constituents of recycled aggregates**

Aggregate Type (20 mm)	Constituents (% by mass)					
	Rock/Concrete	Brick	Tile	Clay	Metal	Other impurities
RA1-RA5	100	-	-	-	-	-
RA6	98.2	0.8	0.6	0.2	0.15	0.05
RA7	96.05	2.1	0.75	0.35	0.15	0.65
RA8	99	0.8	0.2	0	0	0
RA9	96.9	1.6	0.4	0.1	0.1	0.9

### *Aggregate properties*

The constituents and properties of the aggregates used in this study are shown in Table 3-2 and Table 3-3, respectively.

Figure 3-3 shows the grading limits of the fine aggregate required by BS 882-103, and the fine aggregates used in this study are all within the limits. However, the fineness modulus (FM) values of the fine aggregates showed in Table 3-3 indicate that crushed stone fines (FNA1 and FNA2) are much coarser than river sand.

As regards the constituents of RAs, it can be noted from Table 3-2 that RAs collected from the recycling plant generally contains certain amounts of impurities, such as bricks, tiles, glass, asphalt, plastics, wood, gypsum, clay, etc. Taking into account that RAs might be collected from varying sources using different recycling methods (e.g. type and effort of crushers used), the relative proportions of the above constituents may vary greatly.

**Table 3-3 - Aggregate characteristics**

Aggregate type		Particle Size	$SG_{SSD}$	$W_a$	$M_C$	$ACV$ (%)	$TFV$ (KN)	$FM$
		mm	$g/cm^3$	%	%	10-14mm	10-14mm	
<b>NAs</b>	NA1	20	2.66	0.71	0	15.8	259	/
	NA2	20	2.6	1.01	0	21.7	155	/
<b>RAs</b>	RA1	20	2.41	6.38	47.8	19.3	131	/
	RA2	20	2.42	5.18	47.9	19.7	154	/
	RA3	20	2.44	5.36	52	19.5	151	/
	RA4	20	2.45	5.3	62.3	20.3	147	/
	RA5	20	2.46	5.36	69	20.4	155	/
	RA6	20	2.48	3.36	21	22.5	143	/
	RA7	20	2.36	6.14	35.1	23.4	133	/
	RA8	20	2.36	6.44	62	23.9	127	/
	RA9	20	2.49	3.85	22	21.5	149	/
<b>Masonries</b>	Brick	20	1.99	21.74	0	27.1	44	
	Tile	10	2.03	14.82	0	19.1	105	
<b>Fine aggregate</b>	FNA1	5	2.62	0.76	0	/	/	3.28
	FNA2	5	2.63	0.94	0	/	/	2.19
	FNA3	5	2.61	0.44	0	/	/	2.94

From Table 3-3, it can be seen that the most significant difference between NAs and RAs is that RAs usually contain a large amount of attached mortar and old

cement paste, about 20-35% of the total mass for RAs collected from the recycling plant. The percentage is even higher for the RAs crushed from old concrete (to about 62%). This amount is normally related to the properties of the original concrete from which the RA is derived and the production process of the RA.

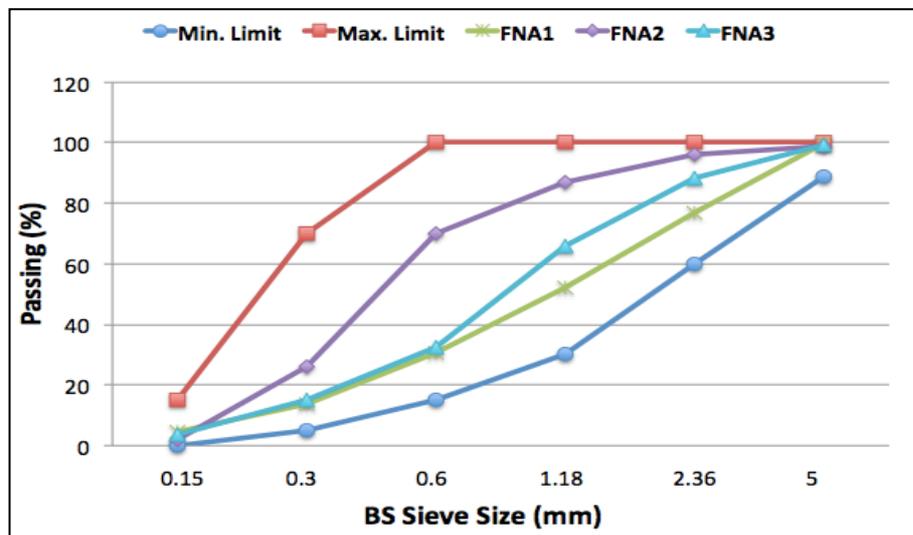


Figure 3-3 - Sand grading according to BS 882

Due to the presence of large amounts of old attached mortar, lower SSD specific gravity ( $SG_{SSD}$ ), higher  $W_a$  and inferior strength are the primary features of RA when compared with NA, which can be seen clearly from Table 3-3. It can be also noticed that the strength of RAs used all satisfy the requirement of BS 882 for aggregate used for concrete production. Some of the values are even comparable with that of the NA2. Different RAs from different sources also

show different strength. Poorer properties can be noticed for the crushed tiles and bricks, with  $SG_{SSD}$  only about  $2 \text{ g/cm}^3$  and the  $W_a$  value over 10%. The case is more obvious for the crushed bricks, with ACV and TFV 27.1% and 44 kN, respectively.

### ***Water***

Standard tap water is used for preparing all the concrete mixes. Distilled water is used for the chloride diffusivity test of concrete.

### ***Superplasticizer***

Superplasticizer, obtained from Hong Kong Grace Construction Products Limited with a density of  $1,210 \text{ kg/m}^3$ , is used to adjust the workability of fresh concrete.

## **3.2.2 Concrete mixtures**

### ***Mix proportions***

As introduced above, 3 groups with a total of 46 mixes of concrete are prepared to examine the properties of RAC from different perspectives. The details mix proportions of the concrete mixtures made are shown in Table 3-4 - Table 3-6.

(1) Case I - RAC made with RAs from Group 1

For RAs of Group 1, NAC made with NA1, namely NAC, is firstly prepared with C of 440 kg/m<sup>3</sup> and a W/C of 0.35. Then 100% of RA1-RA5 is used as a volume replacement of NA1 to produce recycled high strength concrete (RC1-RC5), respectively. For all six mixes, CSF with a FM value of 3.28 is used. The mix notations of the mixes are shown in Table 3-4.

(2) Case II - RAC made with RAs from Group 2

For the RAs of Group 2, four series of concrete mixes are prepared using NA2 and three types of RAs (RA6-RA8). In each series, four concrete mixes with different 28-day target cube strength between 30MPa and 80MPa are prepared, and the corresponding W/C ranges from 0.68 to 0.34. For each concrete mix, NC is prepared with 100% NA, while RC6, RC7 and RC8 are made with 100% RA1, RA2 and RA3, respectively. For concrete made with different types of aggregates, appropriate amounts of superplasticizer are used to achieve a similar slump value of 70-90 mm for Series I to Series III and 120-150mm for Series IV. River sand with a FM value of 2.19 is used in all the 16 mixtures.

(3) Case III - RAC made with RAs of Group 3

For RAs of Group 3, crushed bricks and tiles are added respectively as a constituent of RA to prepare concrete mixtures. In part I, the control concrete made with only NA1 as coarse aggregate, namely Control, is firstly prepared with a C of 380 kg/m<sup>3</sup> and a W/C of 0.5. Then crushed bricks and tiles are used as 5, 10, 15% by volume replacement of NA1, respectively. The produced concrete are named as B(T)5, B(T)10 and B(T)15, respectively. In part II, NAC made with only NA2 as coarse aggregate, namely r0, is prepared with a C of 370 kg/m<sup>3</sup> and a W/C of 0.5. RA9 is used as 0, 50, 100% by volume replacements of NA to produce RAC (r0, r50 and r100). On this basis, crushed bricks and tiles are employed as added masonry, respectively. The volume replacement ratios of RA by crushed brick and tile are 0, 5, 10, 15% and 0, 5%, 10%, respectively. The mix notations of the mixes are shown in Table 3-6.

**Table 3-4 - Mix proportions of concrete mixtures of Case I**

Notation	W/C	Mix Proportion (kg/m <sup>3</sup> )				
		Water	Cement	CSF	NA	RA
NAC	0.35	155	440	666	1166	0
RC1	0.35	155	440	666	0	1070
RC2	0.35	155	440	666	0	1077
RC3	0.35	155	440	666	0	1083
RC4	0.35	155	440	666	0	1090
RC5	0.35	155	440	666	0	1094

A “Crocker Brand” pan mixer with a maximum capacity of 0.11 m<sup>3</sup>, shown as

Figure 3-4, is used to prepare all the mixes. For each concrete mixture, the mixing procedures are as follows:

- Coarse aggregate (20mm and 10mm), cement, and fine aggregate are put into the mixer sequentially and dry mixing for 2 minutes
- Water with superplastizer is added to the mixer with another 2 min of mixing
- Flipping the concrete around the edge of the mixer manually to provide the water can be absorbed by the cement and aggregate uniformly
- Immediately after that, further mixing for 1 minute to ensure uniformity of the concrete before slump test.

**Table 3-5 - Mix proportions of concrete mixtures of Case II**

Notion	Mix	V (%) <sup>1</sup>	Proportions (kg/m <sup>3</sup> )				
			Cement	Water	Sand	10mmCA <sup>2</sup>	20mmCA <sup>2</sup>
<b>Series I</b> <b>W/C=0.68</b>	NC30	0				376	752
	C30RA6	100	300	205	697	366	709
	C30RA7	100				340	687
	C30RA8	100				343	684
<b>Series II</b> <b>W/C=0.51</b>	NC45	0				381	762
	C45RA6	100	350	180	706	371	718
	C45RA7	100				345	696
	C45RA8	100				348	693
<b>Series III</b> <b>W/C=0.44</b>	NC60	0				359	718
	C60RA6	100	425	185	696	350	678
	C60RA7	100				325	657
	C60RA8	100				328	654
<b>Series IV</b> <b>W/C=0.34</b>	NC80	0				726	363
	C80RA6	100	485	165	685	700	339
	C80RA7	100				650	329
	C80RA8	100				655	327

<sup>1</sup>V: replacement ratio of NA by RA; <sup>2</sup>CA-coarse aggregate.

### ***Specimens casting and curing***

Then all specimens are cast in steel moulds and compacted using a vibrating table. The 100 mm cubes and 70×70×285 mm prisms are adopted to test the compressive strength and drying shrinkage of concrete, respectively. While the 100×200 mm cylinders are used to evaluate the splitting tensile strength, static modulus of elasticity and chloride-ion penetration of concrete. The specimens are demolded after curing for 24 hours at a controlled laboratory environment, and then three cube specimens are used to test the 1-day compressive strength immediately, the rest of the specimens are cured in a water curing tank (Figure 3-5) at 27±1 °C until the corresponding test ages are reached.

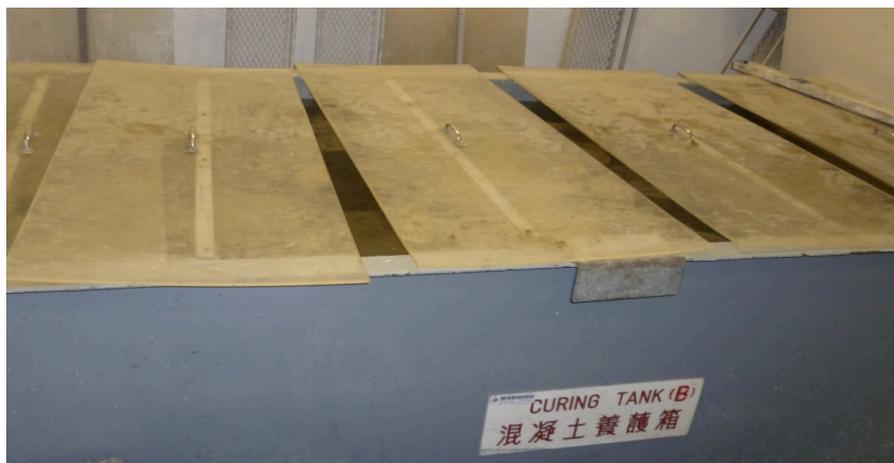
**Table 3-6 - Mix proportions of concrete mixtures of Case III**

Sources	Notation	RA (%)	Masonry (%)	Constituents (kg/m <sup>3</sup> )						
				Water	Cement	Sand	NA	RA9	brick	tile
<b>Part I</b>	Control	0	0	190	380	710	1110	0	0	0
	T5	5	100	190	380	710	1055	0	0	44
	T10	10	100	190	380	710	999	0	0	88
	T15	15	100	190	380	710	944	0	0	132
	b5	5	100	190	380	710	1055	0	43	0
	b10	10	100	190	380	710	999	0	86	0
	b15	15	100	190	380	710	944	0	129	0
<b>Part II</b>	ro	0	0	185	370	732	1090	0	0	0
	r50	50	0	185	370	732	545	463	0	0
	r100	100	0	185	370	732	0	924	0	0
	b5r50	50	5	185	370	732	545	463	18	0
	b5r100	100	5	185	370	732	0	924	37	0

b10r50	50	10	185	370	732	545	463	40	0
b10r100	100	10	185	370	732	0	924	81	0
b15r50	50	15	185	370	732	545	463	63	0
b15r100	100	15	185	370	732	0	924	125	0
T5r50	50	5	185	370	732	545	463	0	23
T5r100	100	5	185	370	732	0	924	0	46
T10r50	50	10	185	370	732	545	463	0	48
T10r100	100	10	185	370	732	0	924	0	94



**Figure 3-4 - “Crocker” concrete mixer**



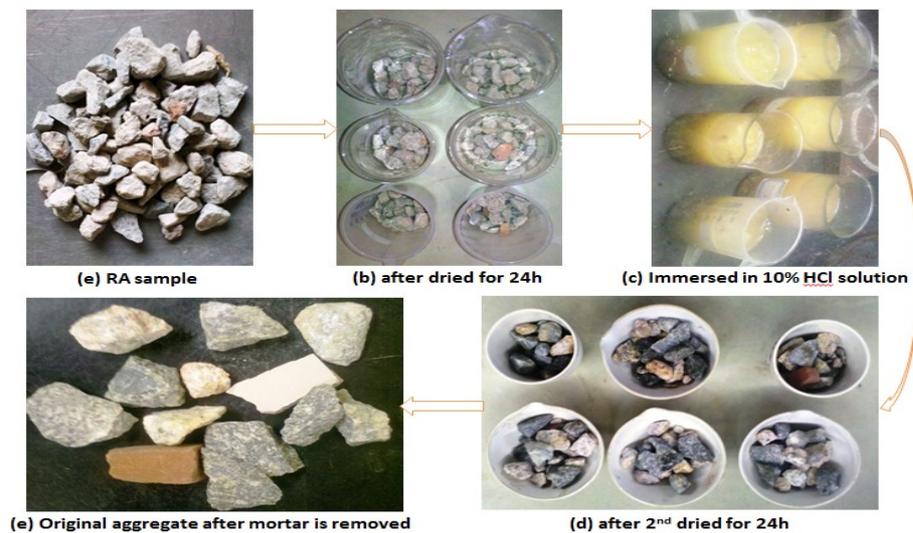
**Figure 3-5 - water curing tank**

### 3.2.3 Test methods

## ***Testing of aggregate***

### (1) Composition of recycled aggregate

The main composition of NA and fine aggregates is crushed stone or river sand. However, the composition is more complex for RAs, which may contain large amounts of attached old mortar. Besides, RAs 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 seriously deteriorate the quality of RA. So the determination of RA composition is very important. In this study, only the RAs of 10-20 mm are used to measure/qualify the masonry and impurity contents according to BS 8500 Part 2.



**Figure 3-6 - Test procedures of mortar content of coarse aggregates**

### (2) Mortar content

As there is no standard method in measuring old cement mortar amounts in RAs,

the test of the  $M_C$  is based on a hydrochloric acid dissolution method (Yagishita et al 1994) as shown in Figure 3-6:

- Firstly, the aggregate samples with particle size of 5-10 mm or 10-20 mm, after washing by distilled water and sieving to remove ad fine particle, are dried in an oven at a temperature of 105 °C for 24h.
- Then, appropriate amount of the sample ( $m_1$ ) is taken and immersed in a solution of 10% hydrochloric acid for 8h.
- Next, the sample is washed again by water to remove the loose particles, and dried in an oven at a temperature of 105 °C for 24h.
- In this way, most of the attached cement mortar on the RAs can be easily removed, and the remaining mortar can be removed manually by a hammer and a steel brush.
- The sample is sieved through a 5mm sieve to obtain the mass of the original aggregate ( $m_2$ ).
- The mortar content is calculated using Equation (3-1). For each type of aggregate, 6 samples are tested to obtain the average value.

$$M_C (\%) = (m_1 - m_2) / m_1 \times 100 \quad (3-1)$$

### (3) Physical properties

The physical properties of all aggregates investigated in this study, such as

aggregate grading,  $SG_{SSD}$  and  $W_a$ , are quantified according to BS 882.

For river sand and crushed stone fines, the gradation varies largely. The method of BS 882-103 is used to determine the grading of the two types of fine aggregate.

Their FM values are also calculated.

### ***Mechanical properties***

ACV and TFV are used as the indexes to determine the mechanical properties of coarse aggregates. BS 882-110 and BS 882-111 are adopted as the approaches to quantify the ACV and TFV of each type of aggregate (10-14mm), respectively.

### ***Testing of concrete***

#### (1) Slump test

In this study, the slump test is carried out according to BS 1881-102. For concrete made with RAs, appropriate amounts of superplasticizer are added to achieve a similar slump value as that of the corresponding normal aggregate concrete.

$$\rho = (m_2 - m_1) / m_1 \times 1000 \quad (3-2)$$

(2) Density test of hardened concrete

The density test of hardened concrete for NAC and RAC are according to BS 1881: Part 114 by using the equipment as shown in Figure 3-7. The detailed procedures are as follows:

- Immediately after the specimen (assumed to be in wet condition) are removed from the curing tank, it is put into the stirrup and then immersed into the water to obtain the mass of the specimen in water,  $m_1$  (in kg)
- Then remove the specimen from water and wipe off surplus water from its surface using a dry towel, followed by weighing in a balance,  $m_2$  (in kg)
- Calculate the density of the specimen  $\rho$  (in  $\text{kg/m}^3$ ) using Equation (3-2). For each group, 3 specimens are tested to obtain the average value.



**Figure 3-7 - Equipment for density test**



**Figure 3-8 - Compression machine**



**Figure 3-9 - Specimen and machine used for elastic modulus test**

### (3) Compression and tensile splitting strength test

The  $f_{cu}$  and  $f_{tc}$  of the concrete are determined using a compression machine (Figure 3-8) with a loading capacity of 3000kN. They are determined in accordance to BS 1881-116 and BS 1881-116, respectively. The load applied in the compressive and splitting tensile tests are kept at a constant rate of

0.2MPa/sec and 0.85 kN/sec, respectively. For each mix, three cube and two cylinder specimens are tested at the corresponding test days to obtain the average value for the  $f_{cu}$  and  $f_{tc}$ , respectively.

(4) Static modulus of elasticity test

The cylinders as shown in Figure 3-9 used for determining the static modulus of elasticity are capped by using a sulphur-clay mixture. The  $E_c$  of the concrete, determined as the mean value of the results of two specimens, is assessed following the procedure described in ASTM C 469 using a Denison compression machine (Figure 3-9) at the test ages of 28 and 90 days, respectively.

(5) Chloride-ion penetration test

The chloride diffusivity of concrete is determined in accordance with ASTM C1202. The penetration tests are performed by using two 100×50 mm cylinder specimens, which are cut from the cast 100×200 mm cylinder specimens. The test is carried out at the ages of 28 and 90 days, respectively.

Prior to the test, the surface of each cylinder is coated with two layers of epoxy.

The coated cylinders are evacuated in a desiccator (Figure 3-10) using a vacuum

pump for 6 hours, and then soaked in distilled water for 18 hours with the vacuum pump still running. Thereafter, the chloride permeability can be determined by using the testing apparatus shown in Figure 3-11. The detailed procedures are as follows:

- The water saturated cylinder with the coated surface is firstly placed in the apparatus;
- One end of the cylinder is exposed to a 3% sodium chloride (NaCl) solution, while the other end is exposed to a sodium hydroxide (NaOH) solution;
- Applying a constant potential of 60V across the ends of the cylinder;
- Then the current across the cylinder is recorded every 30 minutes for the 6-hour test period;



**Figure 3-10 - Desiccator with a vacuum pump**

According to Equation (3-3), the total charge passed in coulomb during the 6-hour test period can be calculated.



**Figure 3-11 - Apparatus for chloride permeability test**

$$Q=900(I_0+2I_{30}+2I_{60}+\dots+2I_{300}+2I_{330}+2I_{360}) \quad (3-3)$$

where  $Q$  = charge passed (coulombs);

$I_0$  = current measured immediately after the potential is applied, and

$I_t$  = current measured at  $t$  min after the potential is applied.



**Figure 3-12 - Apparatus for drying shrinkage test**

#### (6) Drying shrinkage test

The drying shrinkage test in this study is carried out in accordance with ASTM C157. Immediately after the concrete prisms are demolded, the initial length of each specimen is determined by using the apparatus as shown in Figure 3-12.

Then the specimens are placed in a drying-chamber, with the temperature and relative humidity kept at  $23 \pm 2$  °C and  $50 \pm 5$  %, respectively, until the next measurements at other test ages.

### 3.3 ANN APPLICATION

In this research study, large amounts of data related to the  $f_{cu}$  and  $E_c$  of RAC are collected from different published literatures for conducting ANN models with generalization ability.

Firstly, to examine whether ANN is suitable for use in modeling the properties of RAC, ANN methods developed by previous researchers are adopted to build models to evaluate the properties of RAC documented in some published literatures.

Then large amounts (more than 300) of datasets are collected from different published literature for constructing improved ANN models for the  $f_{cu}$  and  $E_c$  of RAC, respectively. The improved ANN models are then applied to predict the corresponding properties of concrete mixtures prepared in this study. The predicted results are also compared with the experimental test results. Sensitivity analysis is finally conducted to examine the influence of each input variable on the  $f_{cu}/E_c$  of RAC after the construction of the models.

The developed ANN models are further improved through including more

aggregate characteristics as input variables to investigate the significance of each aggregate characteristic and to determine the best combinations of factors that may affect the  $f_{cu}$  and  $E_c$  of RAC.

## **CHAPTER 4: EXPERIMENTAL TEST RESULTS**

### **4.1 INTRODUCTION**

This chapter presents and discusses the experimental results of aggregate characteristics and the properties of hardened concrete made with these aggregates. The influence of different sources of RAs on the properties of concrete is analyzed.

### **4.2 TEST RESULTS OF CASE I**

To obtain RAs of different qualities, five parent concretes with 28-day compressive strength from 30MPa to 85MPa were prepared and then crushed by hammer after 90 days' curing to sizes of 5-10mm and 10-20mm, respectively. To examine the qualities of these RAs, their physical properties, such as  $M_C$ ,  $W_a$  and density, as well as mechanical properties like ACV and TFV, were tested. The influence of RAs of different qualities on the properties of RAC was also investigated. The details of the experimental results are discussed below.

### 4.2.1 Aggregate properties

Figure 4-1(a) shows that the amount of old mortar in the recycled coarse aggregates is large and it constitutes over 45% of the total aggregate by weight. The value increased to nearly 70% with the increase of the target strength of the original concrete. This is mainly because the RA, obtained through crushing old concrete manually by a hammer, may have more residual mortar left on them when compared with that produced by a mechanical rock-crushing machine.

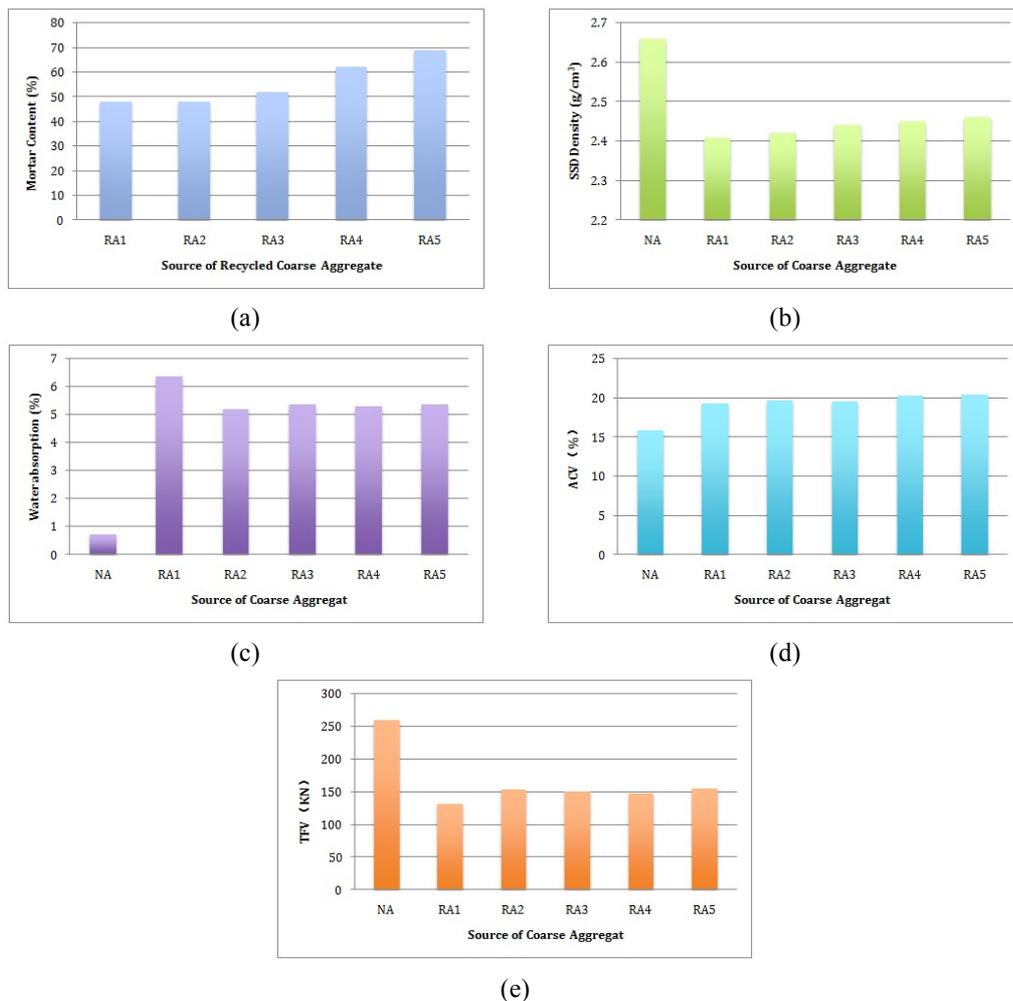


Figure 4-1 - Test results of recycled aggregates

As expected, RAs have higher water absorption values and lower densities, and the specific gravity of RAs increase slightly with the increase of the strength grade of the parent concrete. The above finding is different from that of Padmini et al. (2009) who pointed out that with the increase of parent concrete quality, the density would decrease gradually since lower density mortar would lead to lower density. The difference between the two studies may be attributed to the different sources of parent concrete and different crushing methods used.

Lower density and higher  $W_a$  values than those of NA can be noticed for RA (Figure 4-1(b) and (c)). The densities of RA are about 90% of that of NA and the value increases gradually from RA1 to RA5. The  $W_a$  value of RA2 is the smallest among all the RAs, but is still about 7 times that of NA.

Figures 4-1(d) and (e) show the mechanical properties of the coarse aggregates. It is accepted that the mechanical properties of RA are inferior to that of NA. The TFV of RAs is 60% lower than that of NA used, but the RAs (except RA1) still have TFV similar to NA used in Hong Kong (Kou, 2006).

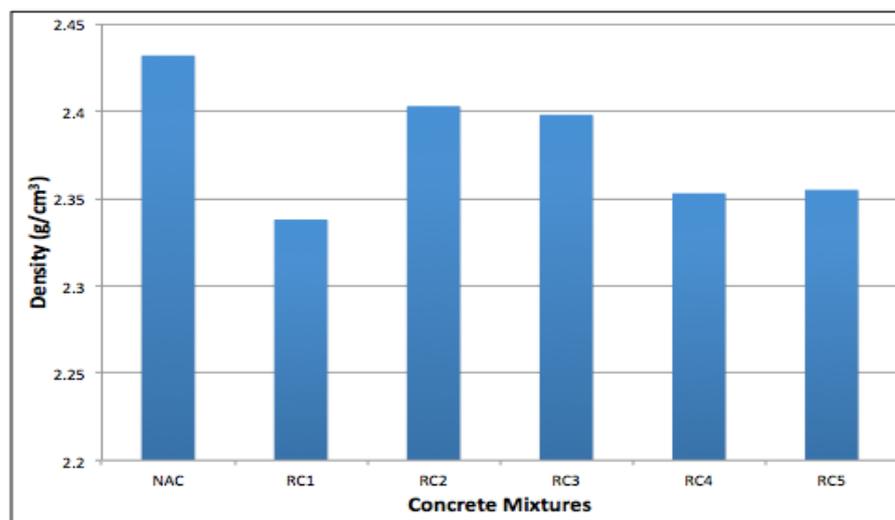
#### **4.2.2 Concrete properties**

The slump value of the concrete prepared with RAs with different qualities can be adjusted to the range of 100-150mm with the addition of appropriate amounts of superplasticizer.

The hardened properties of the new concrete made with NA and RAs of different qualities after 28 days' curing are shown in Table 4-1.

**Table 4-1 - Test results of concrete mixtures at 28 days**

Notation	Density ( $g/cm^3$ )	$f_{cu}$ (MPa)	$f_{tc}$ (MPa)	$E_c$ (GPa)	CT (Coulombs)
NAC	2.432	69.6	4.05	32.3	2376
RC1	2.338	59.4	2.84	26.18	3366
RC2	2.403	69.8	3.79	27.26	3146
RC3	2.407	67.8	4.15	27.05	3126
RC4	2.396	68.7	4.32	26.85	2896
RC5	2.355	62.1	3.62	26.8	3105



**Figure 4-2 - 28d densities of concrete mixtures**

### *Density*

The 28-day density values of the new concrete mixtures are shown in Figure 4-2.

As expected, the hardened densities of all RAC are generally lower than that of NAC due to the lower density of RA. Among all the RAC, the densities of RC3 and RC1 are the largest and the lowest, respectively.

### ***Compressive strength***

The development of  $f_{cu}$  of the new concretes is shown in Figure 4-3. As expected, the compressive strength of NC increases with age in all the concrete specimens.

It can be noticed that the strength of the old concrete plays an important part in affecting the compressive strength of the new concrete mixtures. The minimum  $f_{cu}$  values (about 10 MPa lower than that of NC) are obtained in the concrete made with RA1, which is as expected for its worst quality among all the aggregates investigated. However, the compressive strength of NC made with RA5 is not the highest, just slightly higher than that of RAC1, this is mainly due to the presence of a larger amount of attached mortar in RA5. From Figure 4-4, it is noticed that the  $f_{cu}$  values of RC2 to RC4, (especially RC2) can be comparable to that of NAC after 7-day curing. This may be partly contributed by the angularity of RAs and residual mortar on the surface, resulting in better bonding strength between the new paste and the old mortar.

The results also in line with the previous conclusion (Kou and Poon, 2012) that RAs crushed from higher strength parent concrete can be used to replace 100% NA for preparing HSC, except that in this work CFS is used in both the parent and new concrete.

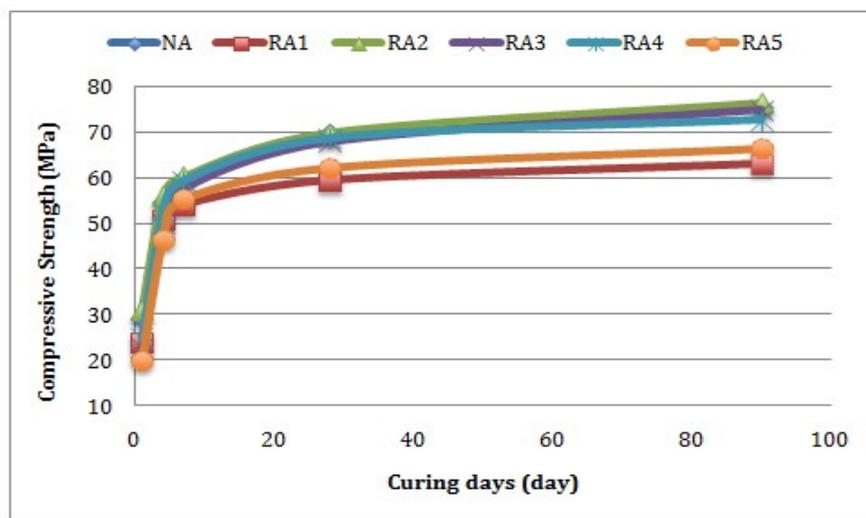


Figure 4-3 - Development of compressive strength of NC with curing ages

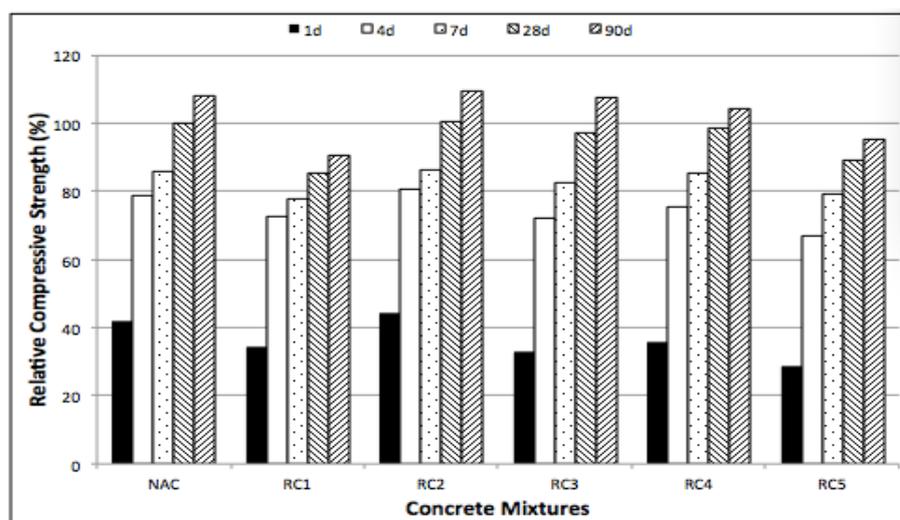


Figure 4-4 - Relative compressive strength of NC with curing ages

### *Tensile splitting strength*

The development of the  $f_{tc}$  is similar to that of the  $f_{cu}$  as shown in Figure 4-5.

Figure 4-6 shows that the  $f_{tc}$  values of RC3 and RC4 after 7 days' curing can be comparable, or even exceed that of NAC. This may be mainly due to the rough surface of the particle of these RAs, which can further improve the microstructure of the ITZ and thus increase the bond strength between the new cement paste and RAs. As shown in Figure 4-7, the relationship between the  $f_{tc}$  and the corresponding  $f_{cu}$  of the concrete mixes is poor, with a correlation coefficient of only about 0.54. This may be attributed to NA and RAs, as well as RAs of different qualities, play different roles in the  $f_{tc}$  and  $f_{cu}$  of RAC.

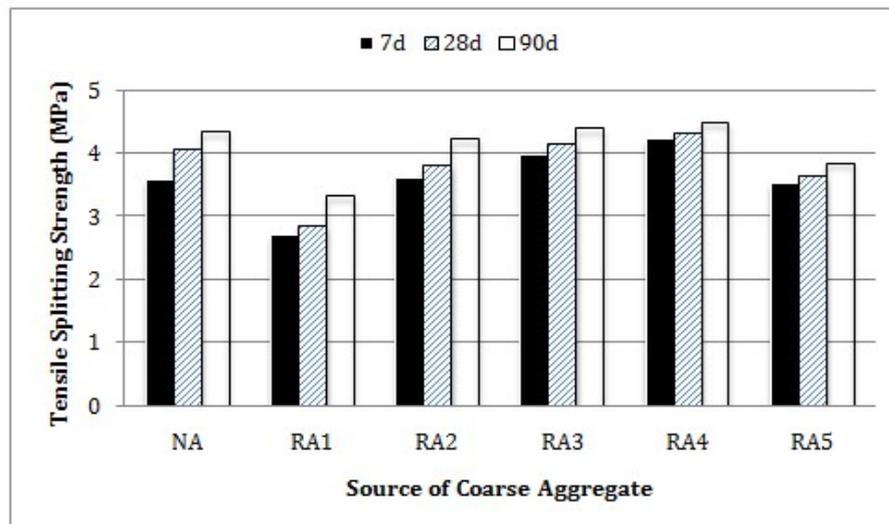


Figure 4-5 - Tensile splitting strength of NC with curing ages

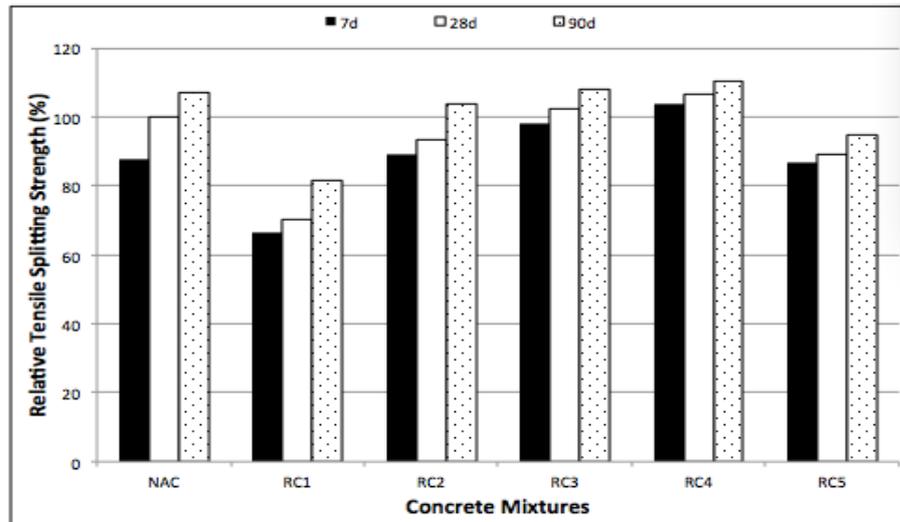


Figure 4-6 - Relative tensile splitting strength of NC with curing ages

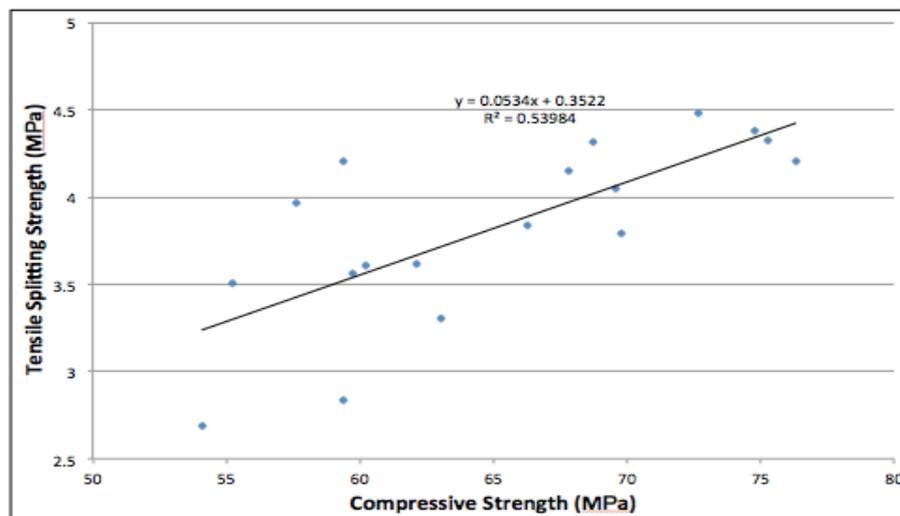


Figure 4-7 - Relationship between the tensile splitting strength and the compressive strength of NC

### *Static modulus of elasticity*

The development trends of the static modulus of elasticity values of the concrete mixes are similar at 28 days and 90 days, which can be seen clearly in Figure 4-8, from which it can be concluded that all the static modulus of elasticity values of RAC decrease sharply to only a little more than 80% of that of the corresponding

NAC. The presence of attached old mortar in RAs is the main reason that leads the reduction in the elastic modulus of RAC, since the elastic modulus of concrete is related to the modulus of elasticity of the aggregates and the cement matrix, and their relative proportions used in the concrete.

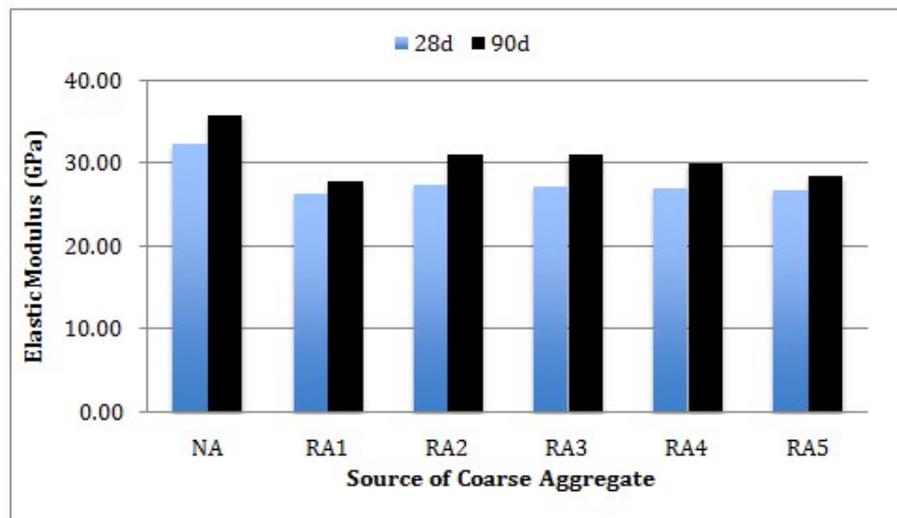


Figure 4-8 - Static modulus of elasticity of NC with curing ages

Figure 4-9 shows the relationship between the  $E_c$  and  $f_{cu}$  of all mixes at both 28 and 90 days. The relationship stipulated by ACI 318-95 and BS EN 1992-1-1 are also plotted to compare the present findings with that of the codes. The regression equation based on the 28 and 90 days experimental results in this study can be expressed as follow:

$$E_c = 0.6929f_{cu}^{0.8836} \quad R^2 = 0.5555 \quad (4-1)$$

where  $f_{cu}$  and  $E_c$  are expressed in MPa and GPa, respectively.

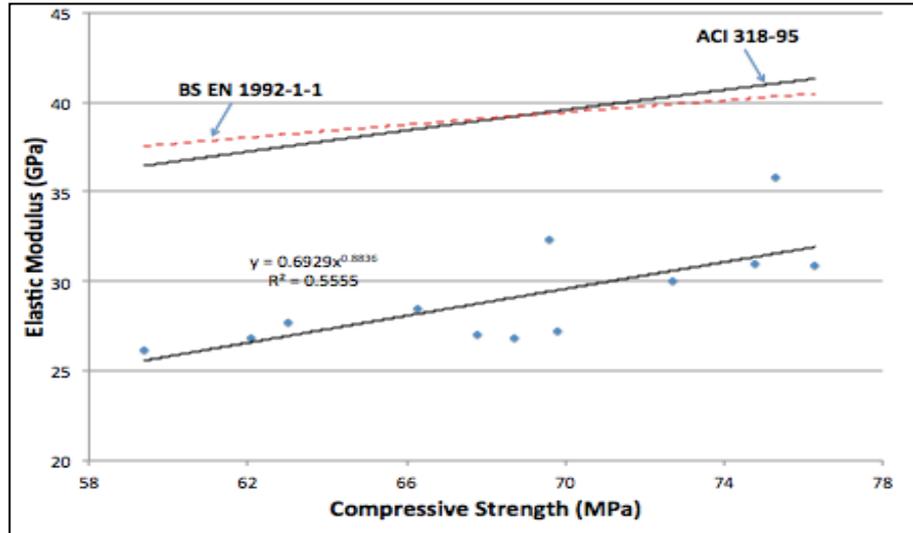


Figure 4-9 - Relationship between the elastic modulus and the compressive strength of NC

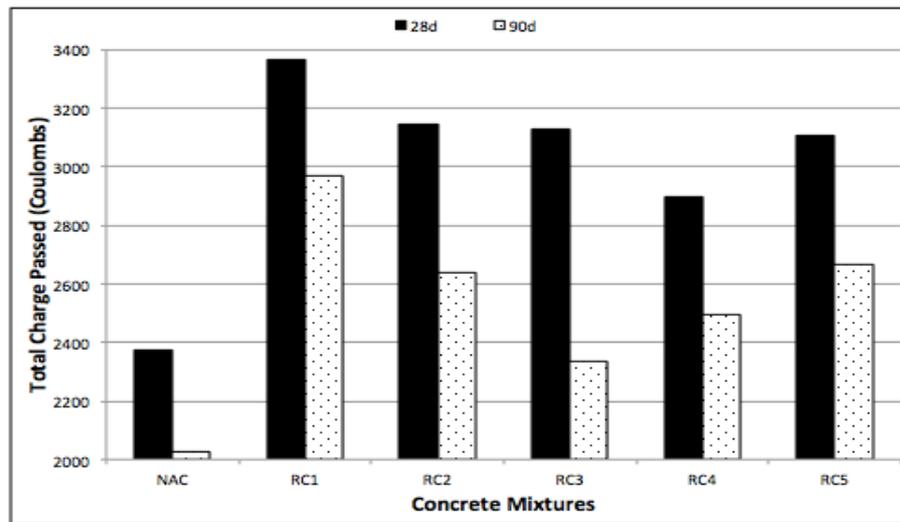


Figure 4-10 - Chloride ion penetration of concrete mixtures

The relationship between  $E_c$  and  $f_{cu}$  based on the experimental results has a poor correlation with  $R^2$  value of only about 0.5555, this is mainly due to the complex nature of RAs. The factors affecting the  $E_c$  and  $f_{cu}$  of RAC may be not the same.

The poor correlation has further proven the premise of this study that it is difficult to model the mechanical properties of concrete made with RAs from

different sources just based on the empirical relationships developed for natural aggregate concrete. It can be also noticed from Figure 4-9 that both ACI 318-95 and BS EN 1992-1-1 overestimate the  $E_c$  values of the RAC.

### ***Chloride ion penetrability***

Similar trends of resistance to chloride ion penetration of the concrete mixes at 28 day and 90 day are shown in Figure 4-10. The results indicate that more charges passed through the concrete made with RAs than that in the control concrete. This can be attributed to the presence of old cement mortar in RAs, leading to higher porosities. Regarding the resistance to chloride ion penetration of all the recycled concrete, RAC3 performs the best, while RAC1 performs the worst as expected.

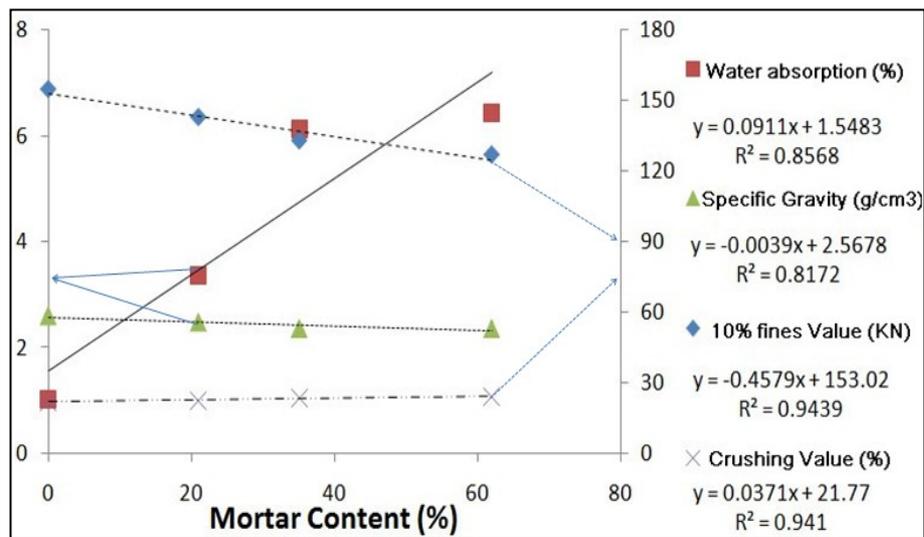
To sum up, RAs crushed from old concrete show higher water absorption and ACV and lower specific density and TFV than those of NA. The new concrete made with RAs performs comparable in compressive strength and splitting tensile strength, but poorer in elastic modulus and resistance to chloride ion penetration, when compared with the control concrete made with NA. RAs from different strength of parent concrete, crushed by hamper, contain large amount of

attached old mortar that play important part on the properties of new concrete, leading its properties more difficult to predict.

### 4.3 TEST RESULTS OF CASE II

#### 4.3.1 Aggregate properties

Table 3-3 shown in Chapter 3 lists the experimental results of the physical and mechanical properties of the aggregates investigated.



**Figure 4-11 - Relationships between mortar content and other properties of aggregates**

Compared with NA, it can be noticed from Table 3-2 that the RA examined in this section generally has lower density and TFV, while their  $W_a$  and ACV are higher than those of NA.

As mentioned above, RAs used in this study can be regarded as a composite material containing unbound stone, virgin aggregate with attached old mortar, hardened mortar and some impurities. The amount of  $M_C$  in RA6 is the lowest, since it was processed in the recycling plant that contains large amounts of crushed rocks. For RA7, the major source is old clean concrete, thus the  $M_C$ , especially in the (5-10mm) fraction, is higher than that of RA6. RA8 has the highest  $M_C$ , since it only underwent one crushing process in the laboratory.

The influence of the quantity of  $M_C$  on aggregate properties is shown in Figure 4-11. The most sensitive indexes are  $W_a$  and TFV. The  $W_a$  of RAs increases drastically while the TFV decrease gradually with the increase in  $M_C$ . It seems that the TFV is more sensitive than ACV in evaluating the strength of RA. It can be explained for the weaker materials in RA are vulnerable to be crushed before the specified load (400kN) is reached. The test results indicate that RA6 has the best quality among all the RAs used in this section. The properties of RA7 and RA8 are nearly the same. More impurities and clay bricks are found present in RA7 while RA8 contains more old mortar, rendering both of them weaker than RA6.

**Table 4-2 - Properties of concrete mixes**

Notion	Mix	$f_{tc}$		$f_{cu}$		$E_c$		$CT$		$shrinkage$
		(MPa)		(MPa)		(GPa)		(Coulombs)		( $10^{-6}$ )
		28d	28d	90d	28d	90d	28d	90d	112d	
Series I W/C=0.68	NC30	2.55	34.5	39.4	25.1	26.6	4651	3627	494	
	C30RA6	2.47	35	39.8	20.85	25.18	5238	3911	449	
	C30RA7	2.4	29.2	34	21.9	22.83	5315	4903	596	
	C30RA8	1.9	27.7	28.4	20.49	21.5	8071	5951	664	
Series II W/C=0.51	NC45	3.16	48.3	53	30.68	31.1	4562	3151	554	
	C45RA6	3.39	47.6	51.3	28.86	30.68	4498	3263	518	
	C45RA7	2.59	42	47	24.46	25.91	4986	4104	650	
	C45RA8	2.58	42.9	46.3	26.55	27.22	6215	4957	604	
Series III W/C=0.44	NC60	3.81	61.6	69.6	32.36	34.5	4196	2826	560	
	C60RA6	3.9	60	67.7	29.42	33.42	3961	3311	611	
	C60RA7	3.74	53.7	55.5	24.61	26.3	5423	4271	709	
	C60RA8	3.42	53.2	58.6	28.5	27.94	5585	4010	635	
Series IV W/C=0.34	NC80	4.28	80.5	88.3	35.43	36.88	2630	2027	515	
	C80RA6	4.65	78.2	84.1	34.76	35.49	2936	2351	529	
	C80RA7	4.1	71.2	74.3	29.52	29.92	3556	2858	644	
	C80RA8	4.16	65.4	73.3	30.62	30.74	5382	3864	682	

### 4.3.2 Concrete properties

Table 4-2 lists the test results of different series of concrete mixes.

#### *Density*

As expected, the densities of the hardened concrete made with RAs are lower than those prepared with NA, which can be seen in Figure 4-12. Good relationships are established between the densities of the concrete and the

corresponding aggregates used, with the correlation coefficients  $R^2$  all exceed 0.85.

### ***Compressive strength***

The comparison of  $f_{cu}$  of concrete made with NA and RAs is shown in Figure 4-13. As expected, the  $f_{cu}$  of the concrete made with RAs are generally lower than that made with NA, whatever W/C is used; besides, the strength of all the concrete made with NA and RAs increase with ages.

It can be noticed from Figure 4-13 that the  $f_{cu}$  of new concrete decreases significantly (over 10% at both 28<sup>th</sup> and 90<sup>th</sup> day) when RA7 and RA8 are used to fully replace NA to produce new concrete. This may be due to the large amounts of old mortar present in them. With the reduction in w/c ratio, it is increasingly difficult for RA7 and RA8 to produce concrete that can satisfy the target strength. For Series IV, the strength values are about 11% and 18% lower than the target strength of 80 MPa when RA7 and RA8 are fully used, respectively. This might be contributed to the poor qualities of RA7 and RA8.

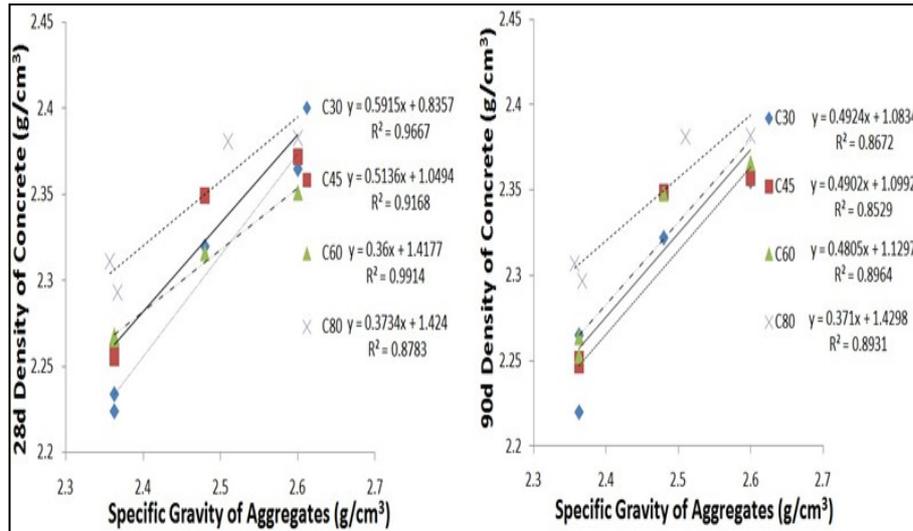


Figure 4-12 - Relationship between specific gravity of aggregates and density of concrete

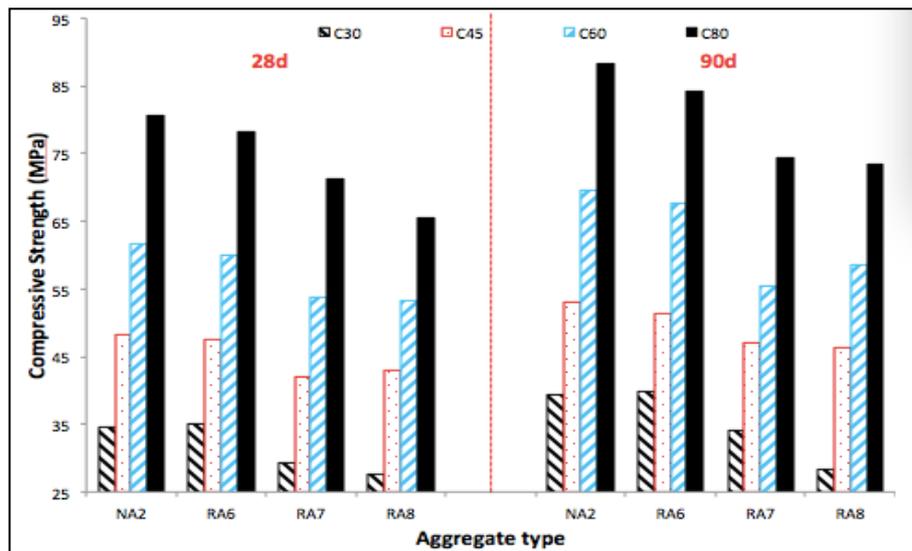


Figure 4-13 - Effect of different aggregates on compressive strength of concrete mixtures

For concrete made with RA6, the produced  $f_{cu}$  value is comparable with that of the control mix (even exceeds the control in the case of C30 concrete). With the increase in target strength, the difference between the strength, for concrete made with NA and RA1, increases gradually to about 2.9% and 4.8% for C80 at 28

days and 90 days, respectively. However, it can be noticed from Table 4-2 that the concrete made with RA6 is still able to reach the target strength of 60MPa after 28 days' curing. So it is feasible to adopt RAs of high quality to prepare concrete with  $f_{cu}$  to that of normal concrete.

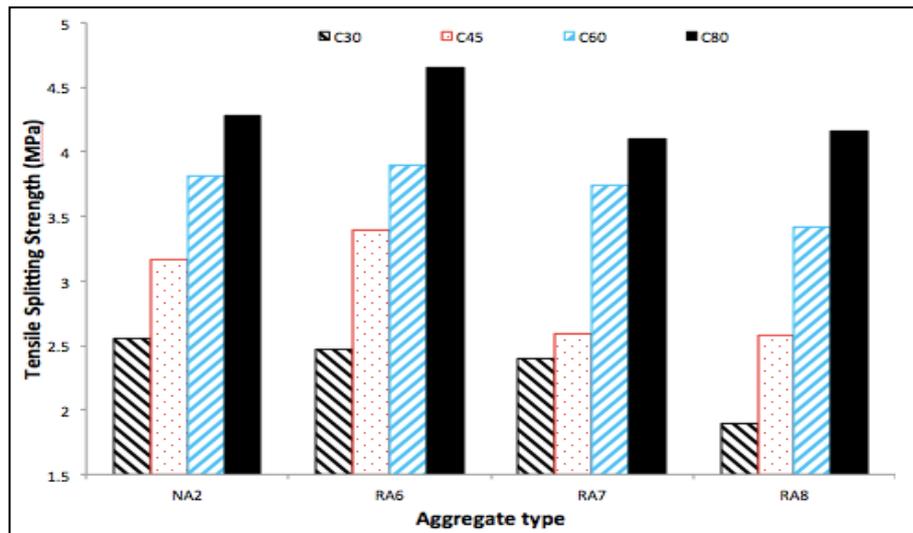


Figure 4-14 - Effect of different aggregates on tensile splitting strength of concrete mixtures

### *Tensile splitting strength*

The results shown in Figure 4-14 indicate that concrete made with RA6 has higher  $f_{tc}$  (except C30) than the corresponding NAC. The increase may be due to the presence of the attached  $M_C$ , which can enhance the bonding between the RA and the new cement paste (Sri Ravindrarajah and Tam 1985). Furthermore, the rough surface of the RAs can further improve the microstructure of the ITZ (Kou and Poon 2008), and thus lead to a high  $f_{tc}$  value.

On the contrary, although RA7 and RA8 have larger amounts of attached mortar than RA6, the excessive amounts of porous mortar lead to a decrease in  $f_{ic}$ .

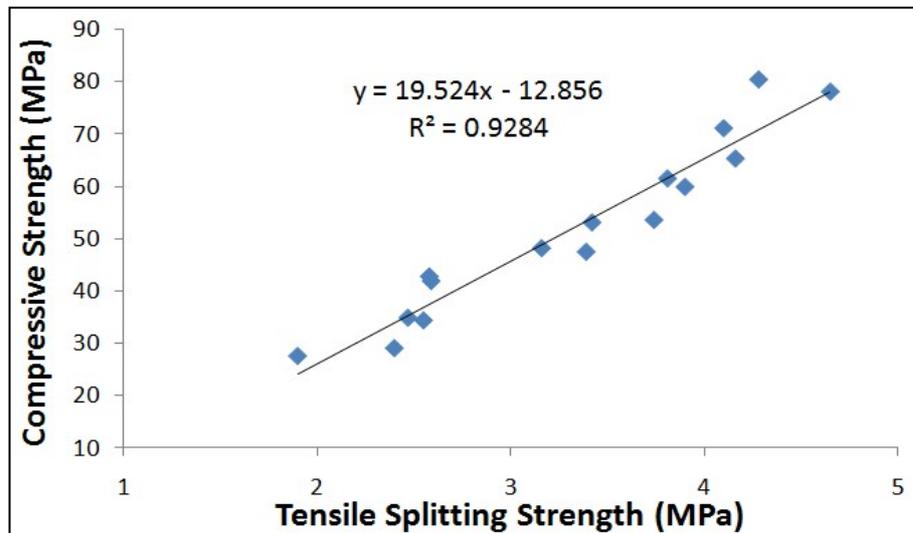


Figure 4-15 - Relationship between 28d compressive strength and tensile splitting strength

As shown in Figure 4-15, the  $f_{ic}$  of concrete has a good correlation with the corresponding  $f_{cu}$ , and the correlation coefficient  $R^2$  reaches to a high value of about 0.93.

### *Static modulus of elasticity*

The results of the  $E_c$  value tests are shown in Figure 4-16. With respect to the value of the control concrete, a significant decline in  $E_c$  values can be noted for

concrete made with RAs and the decrease is more obvious for concrete made with RA7 and RA8.

The  $E_c$  of concrete made with RA6 are almost as good as those made with NA in all the mix series at both 28 and 90 days of curing. As the  $E_c$  of concrete is related to the quality of coarse aggregate, a comparison between mechanical strength (TFV and ACV) of NA and RA6 in Table 3-3 further proves that good quality RA is able to fully replace NA to produce concrete with comparable  $E_c$  value.

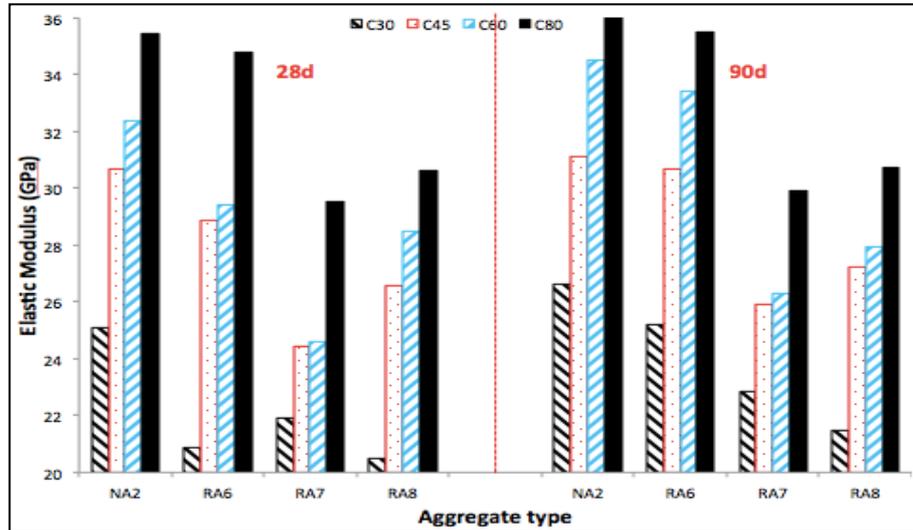


Figure 4-16 - Effect of different aggregates on elastic modulus of concrete mixtures

Figure 4-17 shows the relationship between  $E_c$  and the corresponding  $f_{cu}$  of all mixes at both 28 and 90 days. The regression equation based on the 28 and 90 days experimental results in this study can be expressed as Equation (4-2):

$$E_c = 4.7863f_{cu}^{0.4485} \quad R^2 = 0.8281 \quad (4-2)$$

where  $f_{cu}$  and  $E_c$  are expressed in  $MPa$  and  $GPa$ , respectively.

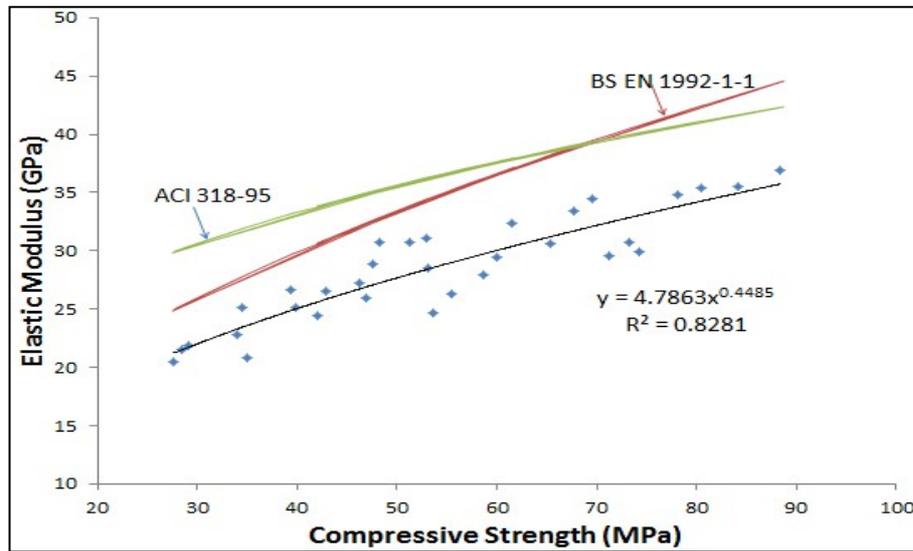


Figure 4-17 - Relationship between the compressive strength and elastic modulus

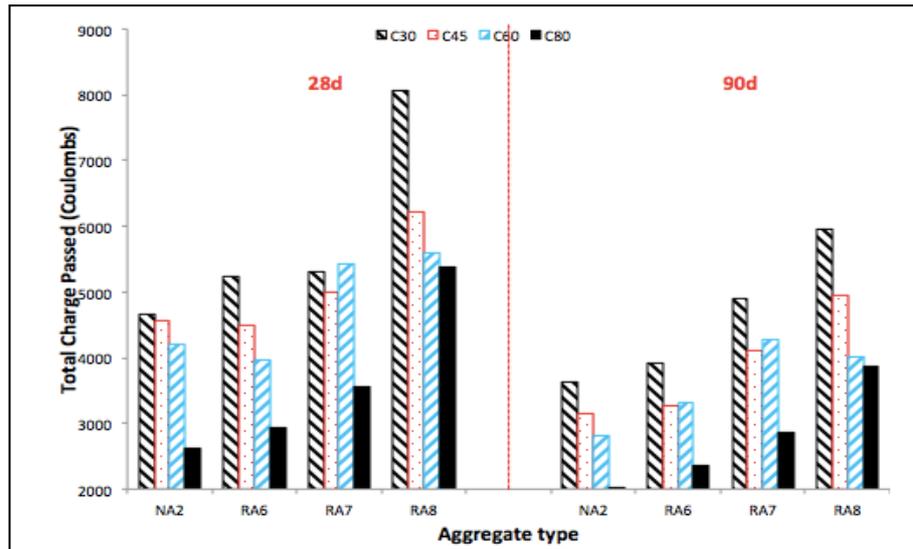


Figure 4-18 - Effect of different aggregates on penetration of concrete mixtures

When aggregates of Group 2 used, the relationship between  $E_c$  and  $f_{cu}$  based on the experimental results has a good correlation with a  $R^2$  value of about 0.8281. However, both ACI 318-95 and BS EN 1992-1-1 still overestimate the  $E_c$  of the RAC, which can be noticed from Figure 4-17. This may be due to that only one parameter, compressive strength, was used to evaluate the corresponding elastic modulus value in such relationships. More parameters, such as aggregate characteristics and cement types, should be considered to be included for better estimation of the properties of the recycled aggregate concrete.

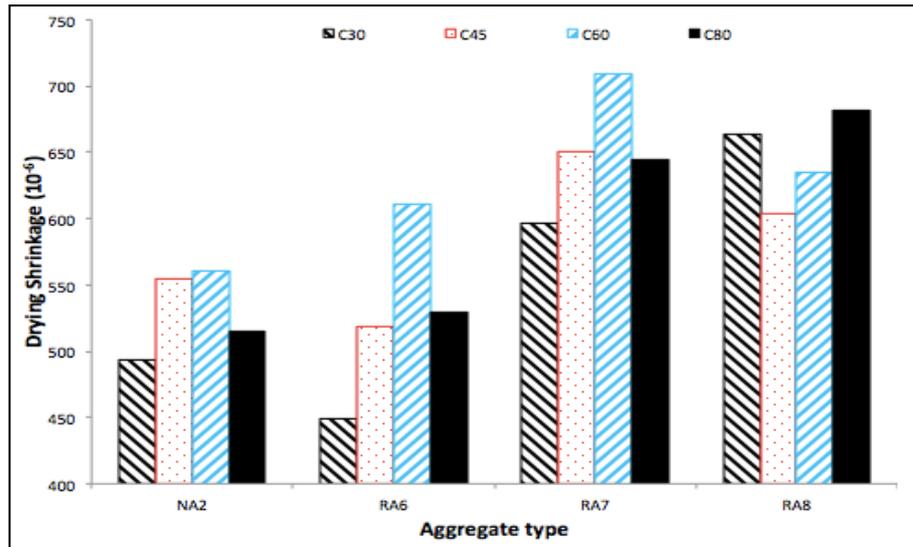


Figure 4-19 - Effect of different aggregates on shrinkage of concrete mixtures

### *Chloride ion penetrability*

Figure 4-18 shows the effect of different types of aggregates and W/C on the resistance of  $\text{Cl}^-$  penetration of the hardened concrete. The results indicate that concrete made with RAs generally have poorer resistance to  $\text{Cl}^-$  penetrability, and the ability of decreases with the trend:  $\text{RA6} > \text{RA7} > \text{RA8}$ . However, it is interesting that the resistance to  $\text{Cl}^-$  penetration of concrete made with RA6 is the best in all the mix series, and can be even comparable with those prepared with NA, especially in Series II and III mixes at 28 days.

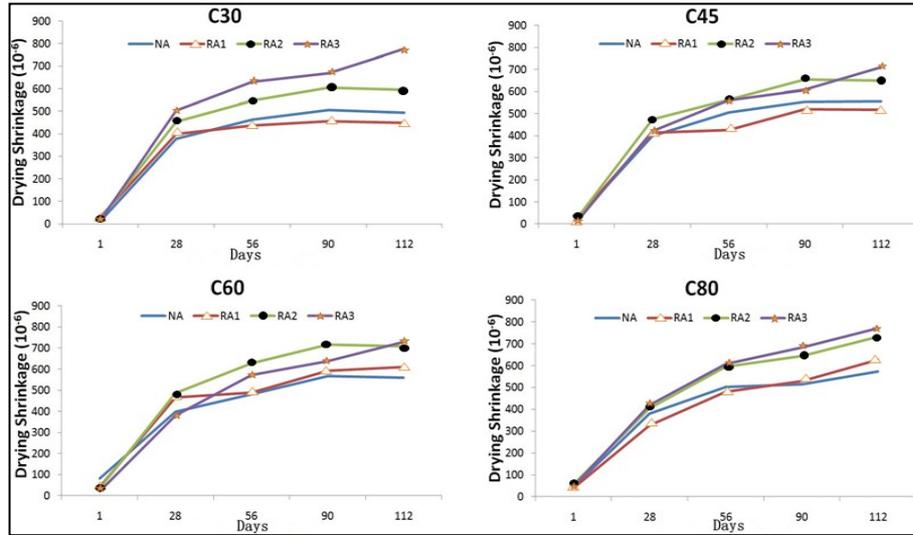


Figure 4-20 - Drying shrinkage of concrete made with different types of aggregates

### *Drying shrinkage*

Figure 4-19 illustrates the effects of NA and RAs on the drying shrinkage of the concrete at 112 days, the trends of which are similar to that on the Cl<sup>-</sup> penetration.

For concrete made with RA of better quality, lower shrinkage values are generally recorded.

The drying shrinkage development of concrete made with different coarse aggregates in all series is presented in Figure 4-20. As expected, the drying shrinkage values of all the concrete mixtures increase with the curing days.

Similar to the Cl<sup>-</sup> test results, the drying shrinkage of concrete made with RA6 is the least in all series, and can be also comparable with that of concrete made with NA.

As a summary, through examining both the RAC prepared with different target strengths and RAC made with various types of RAs, this section has established some relationships between the amount and nature of the attached old cement mortar on the properties of RAs and RAC.

The experimental results show that the mortar contents attached to RAs obtained from different sources vary greatly, and this may be related to original mortar content and the level of prior mechanical crushing received. The presence of residual mortar in RAs leads to their poorer aggregate properties, including lower density and crushing strength values. The results also indicate that RA of good quality can be used to fully replace NA to produce concrete with mechanical and durability properties comparable to those made with NA.

#### **4.4 TEST RESULTS OF CASE III**

This section mainly studies the properties of NAC or RAC incorporated with large amounts of added masonry. The use of 5%, 10% and 15% crushed bricks and tiles as aggregate replacement of concrete mixtures are firstly examined. The test results of concrete made with such mixed aggregates after 28 days' curing

are shown in Table 4-3. Then RA is used to substitute 50% and 100% NA by volume, while crushed clay bricks and tiles are used as the masonry added aggregates as before. The effects of different masonry contents on the properties of new concrete are investigated. The 28 days test results are listed in Table 4-4.

#### 4.4.1 Aggregate properties

In this part, apart from two sources of NA, one source of RA, together with crushed bricks and crushed tiles are also examined. The experimental results of the physical and mechanical properties of the aggregates can be seen in Table 3-3.

**Table 4-3 - Test results of the use of masonry in natural aggregate concrete**

<b>Notation</b>	<b>Density (g/cm<sup>3</sup>)</b>	<b><math>f_{cu}</math> (MPa)</b>	<b><math>f_{tc}</math> (MPa)</b>	<b><math>E_c</math> (GPa)</b>	<b>CI (Coulombs)</b>
<b>Control</b>	2.384	54.4	3.19	31.51	31.51
<b>T5</b>	2.351	54.4	2.97	30.94	30.94
<b>T10</b>	2.325	54.9	3.11	29.14	29.14
<b>T15</b>	2.293	52.5	3.37	27.09	27.09
<b>B5</b>	2.357	54.2	3.22	29.54	29.54
<b>B10</b>	2.331	52.3	3.17	27.5	27.5
<b>B15</b>	2.309	46.9	2.87	23.18	23.18

**Table 4-4 - Test results of the use of masonry in recycled aggregate concrete**

Mixes	$f_{cu}$ (MPa)					$E_c$ (GPa)	
	1d	4d	7d	28d	90d	28d	90d
<b>r0</b>	21.3	/	44.1	50.2	53.3	30.45	33.86
<b>r50</b>	20	40.2	44.1	50.3	53.6	29.58	30.35
<b>r100</b>	18	40.1	43	49.2	51.3	26.78	27.86
<b>b5r50</b>	18.6	38.2 <sup>a</sup>	41.7	48.4	54.1	29.03	30
<b>b5r100</b>	15.9	34.7 <sup>a</sup>	35	44	45.9	27.1	27.9
<b>b10r50</b>	25.3 <sup>b</sup>	/	39.1	47.5	54	27	28.26
<b>b10r100</b>	23.9 <sup>b</sup>	/	34.6	42.4	45.4	26.69	27.85
<b>b15r50</b>	21.6	37.5	38.8	46.7	50.5	24.42	26.14
<b>b15r100</b>	17.5	31.5	33.9	41.1	42.1	24.15	25.58
<b>T5r50</b>	20	34.9 <sup>c</sup>	41.4	49.1	54	27.39	30.13
<b>T5r100</b>	18.5	/	36.5	44.7	47.4	25.69	26.15
<b>T10r50</b>	19.2	37.6	42.5	50.7	52.8	26.72	28.87
<b>T10r100</b>	14.4	28.6	34.4	39.9	42	24.55	25.55

<sup>a</sup>, <sup>b</sup>, <sup>c</sup> measured at the age of 5 days, 2 days and 3 days, respectively.

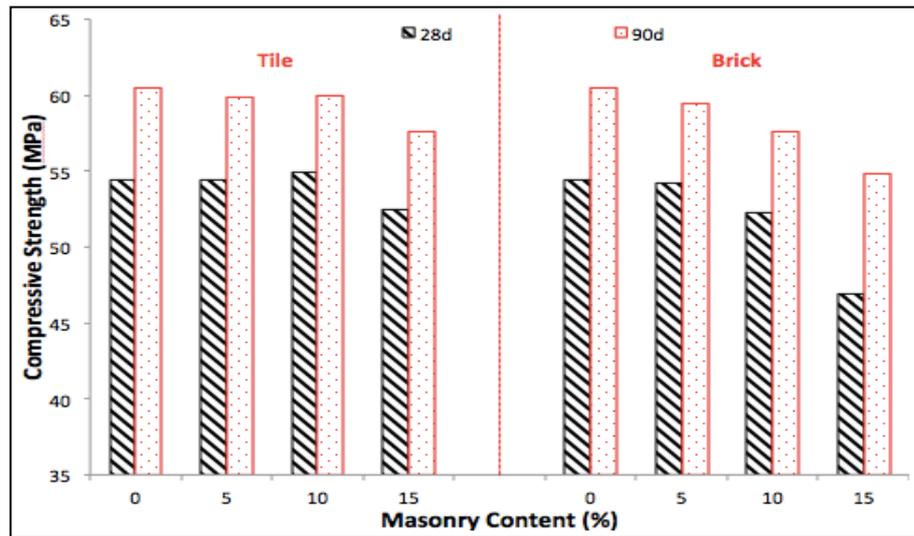
It can be noticed from Table 3-3 that there are also large differences between the properties of the two NAs used, especially in ACV and TFV. Compared with NAs, RA has lower density and TFV, while owns higher  $W_a$  and ACV. These are more obvious to the brick and tile aggregates. The large absorption and weak quality may limit the use of the added masonries in concrete.

#### 4.4.2 Concrete properties

##### *Density*

As shown in Table 4-3, the densities of the hardened concrete made with NA partly replaced by masonries are much lower than that of the control mix. This is

mainly due to the lower density of crushed bricks or tiles relative to that of the crushed granite.



**Figure 4-21- Effect of different masonry contents on compressive strength of natural concrete mixtures**

### ***Compressive strength***

The effect of 0-15% of crushed bricks or tiles on the  $f_{cu}$  of concrete is shown in Figure 4-21. It can be seen from the Figure that the use of 5% and 10% crushed tiles to substitute natural granite is able to produce concrete with the comparable  $f_{cu}$ . The  $f_{cu}$  of concrete made with 15% NA replaced by crushed tiles is only slightly lower than the corresponding control mix, 3.5% and 4.8% at 28 and 90 days, respectively. A trend of gradual reduction in the  $f_{cu}$  of concrete can be noticed when crushed bricks are used to partly replace the granite by volume.

The reduction is larger than that of concrete made with same volume of crushed tiles, about 13.8% at 28days.

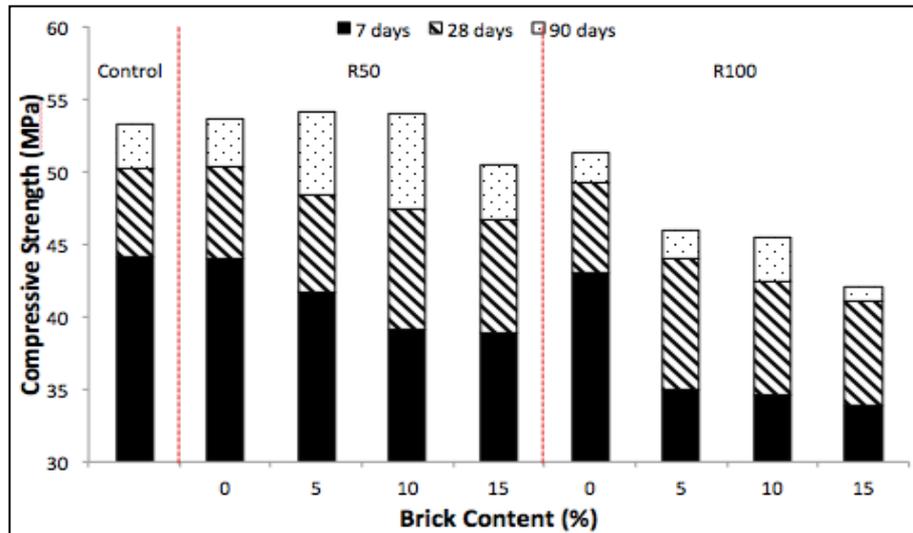


Figure 4-22- Effect of crushed bricks on the compressive strength of RAC

The effects of crushed bricks and tiles on the  $f_{cu}$  of RAC are shown in Figures 4-22 and 4-23, respectively. It can be seen from the two Figures that the use of 50% RA to replace crushed granite can improve the  $f_{cu}$  of concrete slightly, and the strength of RAC are still comparable to the corresponding NAC even 15% bricks or 10% tiles contents. However, a reduction of the strength is noticed when crushed granite is fully substituted by the RA, about 2.2% at 28 days, and the reduction is more significant when RA with larger amounts of masonries added. According to the test results, the 28-day  $f_{cu}$  of RAC made with 15% brick

and 10% tile are about 18.1% and 20.5% lower than that of the NAC, respectively.

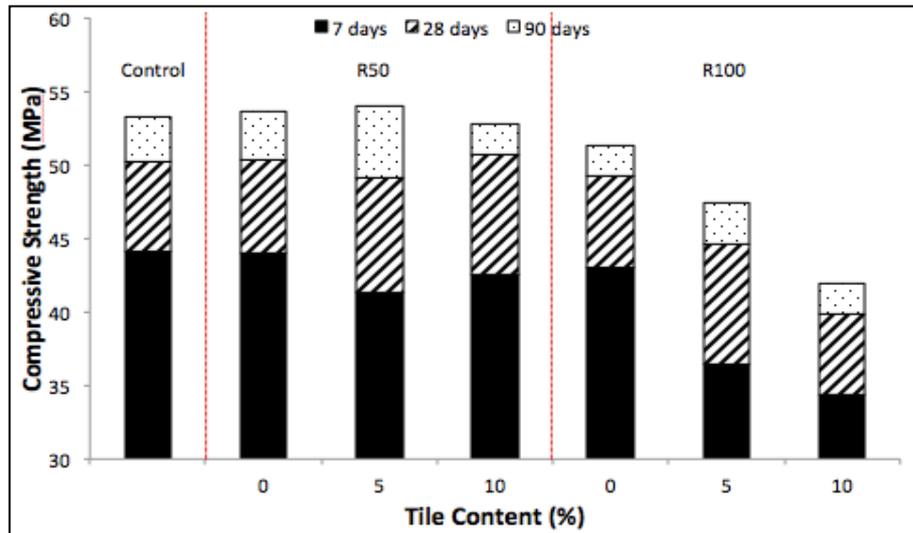


Figure 4-23 - Effect of crushed tiles on the compressive strength of RAC

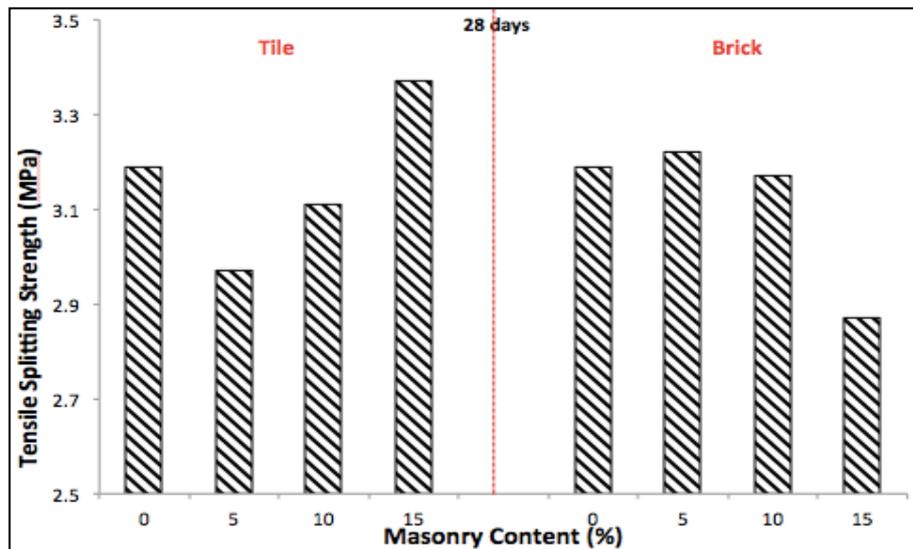


Figure 4-24 - Effect of different masonry contents on tensile splitting strength of natural concrete mixtures

*Tensile splitting strength*

The effect of crushed bricks or tiles on the  $f_{tc}$  of NAC is shown in Figure 4-24.

Opposite development trends are noticed to the concrete made with added bricks and tiles. When using crushed tiles to replace 5% NA, the  $f_{tc}$  of concrete decreases from 3.19MPa to 2.97MPa. However, with the increase of the replacement ratio, the strength increases gradually. The strength of concrete with 15% crushed tiles is even 5.6% higher than the corresponding NAC. While for concrete made with bricks incorporation, the  $f_{tc}$  decreases with the increase in the added brick contents. The lowest strength is about 2.87MPa when the volume ratio of added bricks to total coarse aggregate is 15%.

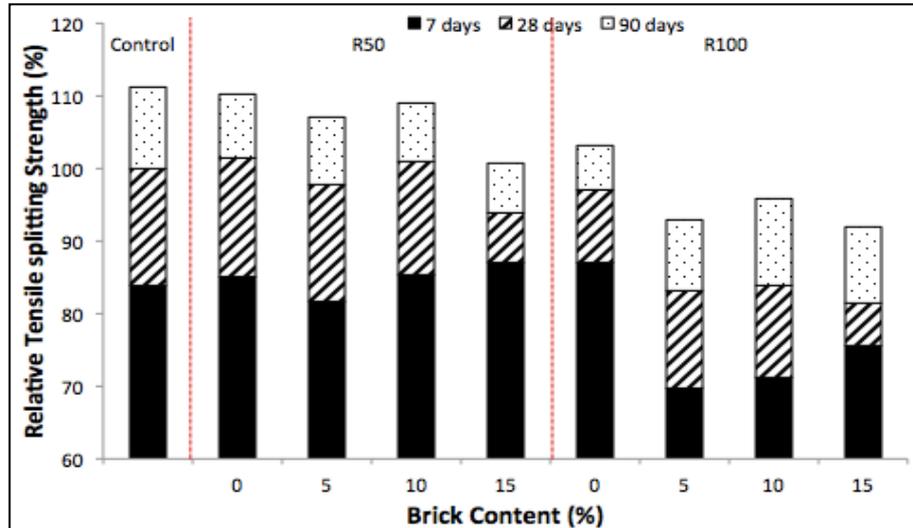


Figure 4-25 - Relative tensile splitting strength of RAC made with added bricks

Figure 4-25 and Figure 4-26 show the ratio of  $f_{tc}$  of RAC made with bricks and tiles at different ages respectively to that of the normal concrete at 28 days. The

$f_{tc}$  of concrete reduces with the increase in the replacement ratio of NA by RA, and the reduction increases when crushed tiles are used as the added masonries in RA, since the smooth surface of the crushed tiles may lead to a weaker bonding and ITZ of the concrete relative to that of the crushed bricks.

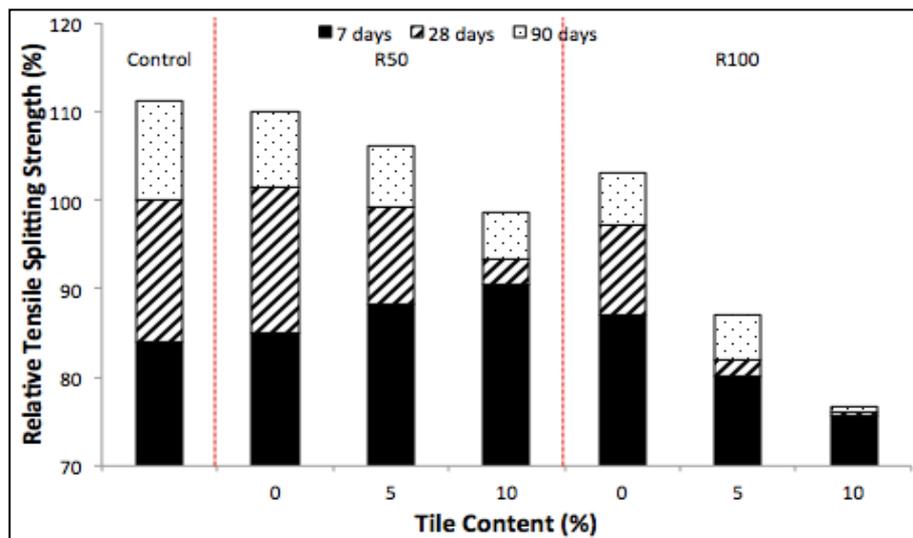


Figure 4-26 - Relative tensile splitting strength of RAC made with added tiles

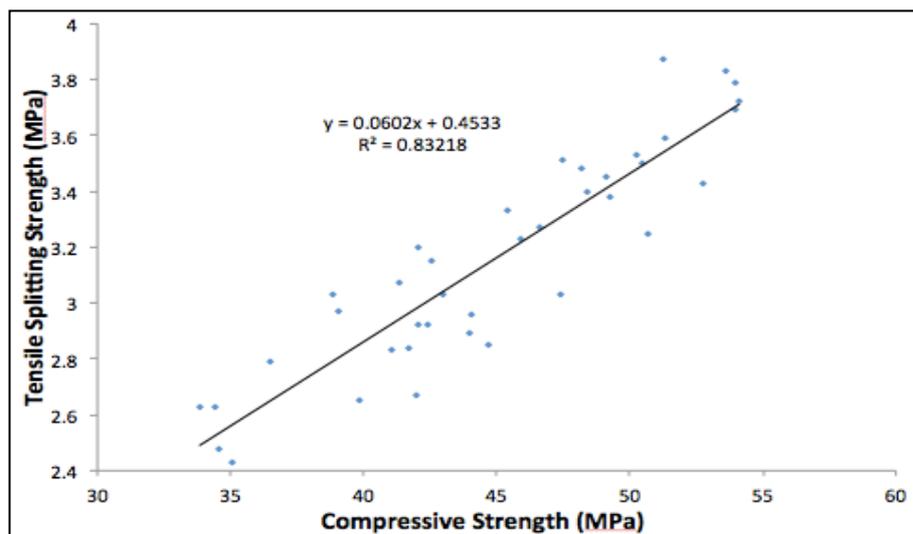


Figure 4-27 - Relationship between the tensile splitting strength and the compressive strength of RAC made with added masonries

As shown in Figure 4-27, the  $f_{ic}$  of concrete has a good correlation with the corresponding  $f_{cu}$ , with a correlation coefficient of about 0.83.

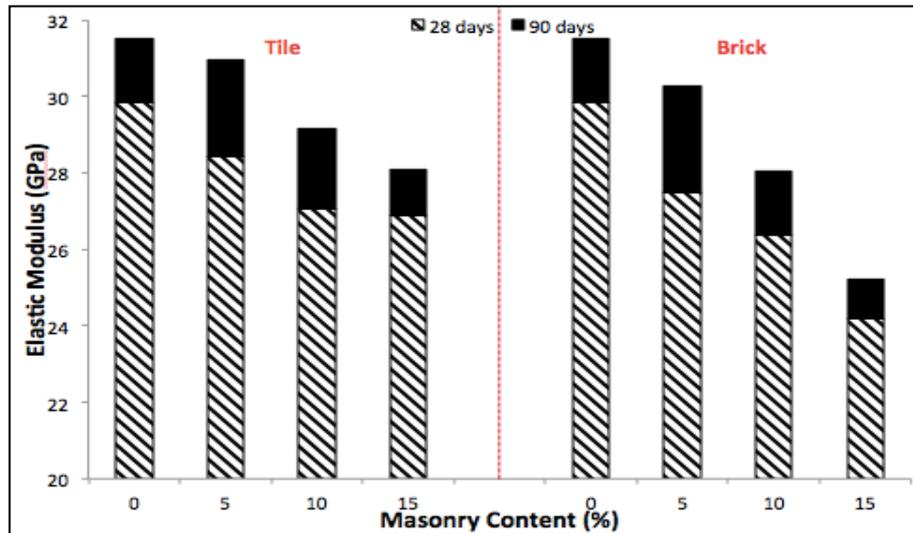


Figure 4-28 - Effect of different masonry contents on elastic modulus of natural concrete mixtures

### *Elastic modulus*

The test results of  $E_c$  of NAC made with the masonry addition are shown in Figure 4-28. The relative  $E_c$  of RAC made with crushed bricks or tiles to that of the corresponding NAC are shown in Figure 4-29 and Figure 4-30, respectively. A sharp decline of  $E_c$  values is noted for the concrete mixtures when crushed granite was replaced by RAs or masonries, and the decrease is more obvious for concrete of the latter one.

Figure 4-31 and Figure 4-32 show the relationship between the  $E_c$  and  $f_{cu}$  of NAC and RAC with the added masonries at both 28 and 90 days. The regression equations between the  $E_c$  values and the corresponding  $f_{cu}$  can be expressed as follows:

$$E_c = 0.4053f_{cu}^{1.0528} \quad R^2 = 0.6825 \quad (4-3)$$

$$E_c = 2.3028f_{cu}^{0.6413} \quad R^2 = 0.5634 \quad (4-4)$$

where  $f_{cu}$  and  $E_c$  are expressed in  $MPa$  and  $GPa$ , respectively.

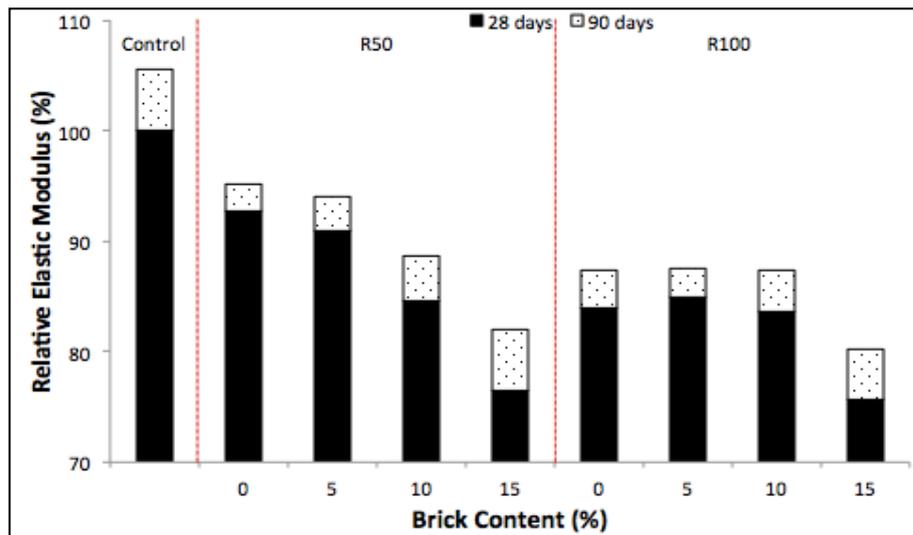


Figure 4-29 - Relative elastic modulus of RAC made with added bricks

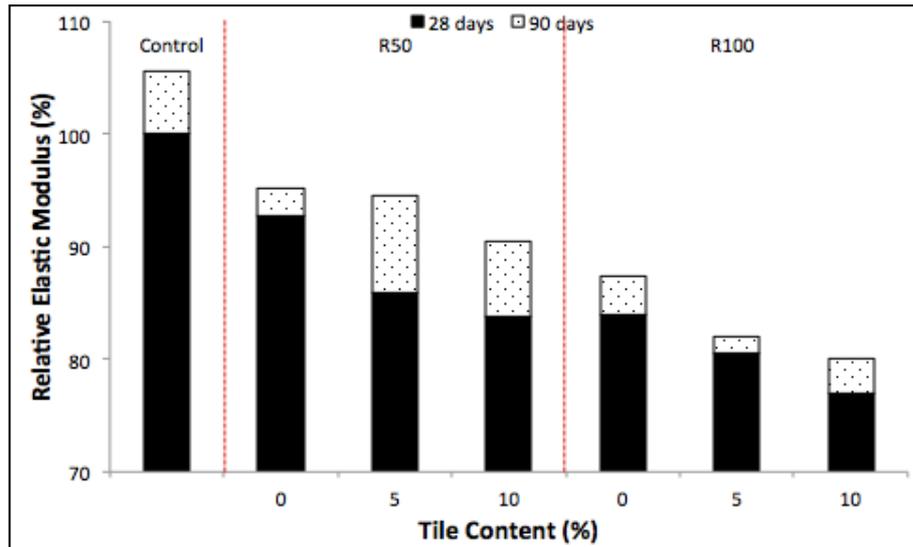


Figure 4-30 - Relative elastic modulus of RAC made with crushed tiles

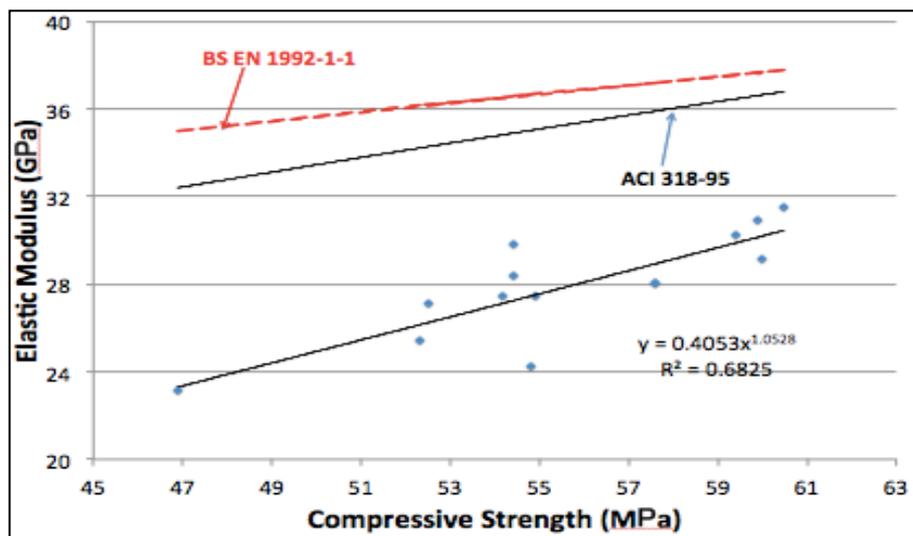
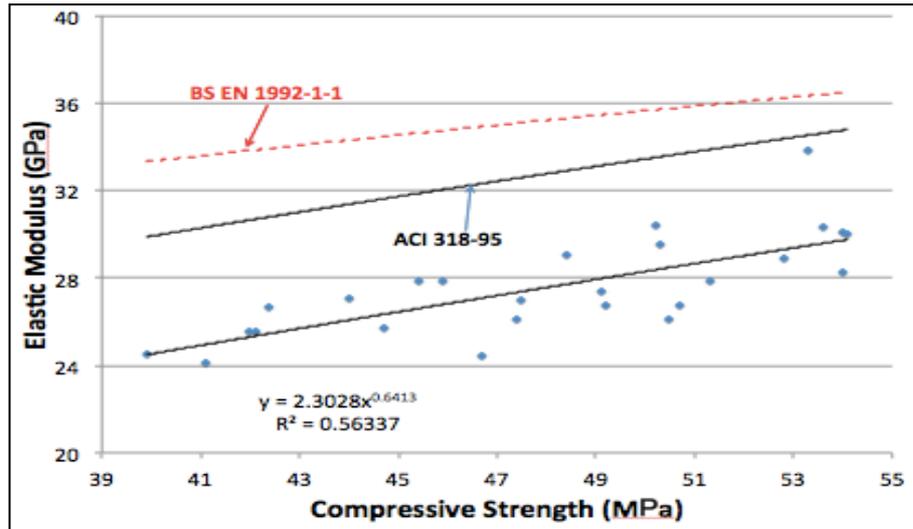


Figure 4-31 - Relationship between compressive strength and elastic modulus of NAC with added masonries



**Figure 4-32 - Relationship between compressive strength and elastic modulus of RAC with added masonries**

Poor correlations shown in Equation 4-3 and Equation 4-4 indicate that the  $E_c$  value of NAC/RAC made with added masonries (Group 3) cannot be expressed effectively by only the corresponding  $f_{cu}$  value. Similar to the results of Case I, this may be due to the more complex nature of mixed aggregates used in this section. Also, it can be noticed from Figure 4-31 and Figure 4-32 that both ACI 318-95 and BS EN 1992-1-1 also overestimate the  $E_c$  of concrete with added masonries.

## 4.5 SUMMARY

This chapter presents the experimental test results of the properties of concrete made with RAs derived from different sources. The properties of aggregates used

in the concrete are also examined. The following conclusions can be drawn based on test results:

**4.5.1 For Group 1 RA: RAs derived from laboratory prepared concrete cubes with different compressive strength (35 MPa-85 MPa):**

- The test results indicate that the properties of RAs are generally poorer than that of NA; RA2 and RA1 own the best and worst properties among the total five RAs examined, respectively.
- The experimental results on  $f_{cu}$  and  $f_{tc}$  indicate that RA2-RA4 can be used to fully replace NA to produce high strength concrete with mechanical properties comparable to concrete made with NA.
- Test results on  $E_c$  point that the elastic modulus values of concrete made with RA of different qualities are lower than that of the corresponding NAC. Both ACI 318-95 and BS EN 1992-1-1 overestimate the  $E_c$  of concrete made with RAs of different qualities.
- Among all the RAC, the resistance to  $Cl^-$  penetration of RAC3 is the best, while that of RAC1 is the worst.

#### **4.5.2 For Group 2 RA: RAs derived from 3 different sources and crushed by different methods:**

- The  $M_C$  attached to RAs obtained from different sources varies largely, and this may be related to original  $M_C$  and the degree of prior mechanical crushing received.
- The presence of residual mortar in RAs leads to their poorer properties, including poorer  $SG_{SSD}$  and mechanical strength.
- The hardened density of concrete made with RA, generally lower than that made with NA, has a good correlation with the  $SG_{SSD}$  of the RA used.
- The experimental results on  $f_{tc}$ ,  $f_{cu}$  and  $E_c$  indicate that RA of good quality can be used to fully replace NA to produce concrete with mechanical properties comparable with that of concrete made with NA.
- The test results on the resistance to  $Cl^-$  penetration show that good quality RA can be used to produce concrete with comparable durability properties.

- Both ACI 318-95 and BS EN 1992-1-1 overestimate the  $E_c$  of concrete made with different sources of RA produced using different methods.

**4.5.3 For Group 3 RA: RAs contain different amounts of added masonries (crushed clay bricks or tiles):**

- The physical and mechanical properties of crushed bricks and tiles are much weaker than those of the NA, and they also cannot be comparable with those of the other RA. This limits their possible use on in concrete.
- Due to the lower  $SG_{SSD}$  of bricks and tiles relative to that of NA, the hardened density of concrete made with the added bricks or tiles is lower than that of the corresponding NAC.
- Both ACI 318-95 and BS EN 1992-1-1 overestimate the  $E_c$  of concrete made with the added masonries.

# **CHAPTER 5: MODELING THE TEST RESULTS BY USING ESTABLISHED RELATIONSHIPS**

## **5.1 INTRODUCTION**

In the last chapter, codes like ACI 318-95 and BS EN 1992-1-1 were found to overestimate the  $E_c$  of RAC made with RAs from different sources. It seems that the above relationships are no longer applicable to concrete made with RA due to the significant difference in properties between RA and NA. This chapter examines the validity of using established relationships to model the  $f_{cu}$  and  $E_c$  of RAC prepared in the laboratory. The predicted results of these relationships are also compared with the experimental test results.

## **5.2 EMPIRICAL EQUATIONS BETWEEN ELASTIC MODULUS AND COMPRESSIVE STRENGTH**

Some empirical relationships have been proposed by researchers (Sri Ravindrarajah and Tam 1985; Dillmann 1998; Dhir et al. 1999; Mellmann 1999) based on their laboratory studies on testing concrete produced with RA. These equations are given as follow.

Sri Ravindrarajah and Tam (1985):

$$E_c = 7.77 f_{cu}^{0.33} \quad (5-1)$$

Dhir et al. (1999):

$$E_c = 0.37 f_{cu} + 13.1 \quad (5-2)$$

Dillmann(1998):

$$E_c = 0.63443 f_{cu} + 3.0576 \quad (5-3)$$

Mellmann (1999):

$$E_c = 0.378 f_{cu} + 8.242 \quad (5-4)$$

where  $f_{cu}$  and  $E_c$  are expressed in MPa and GPa, respectively.

However, the applicability of such equations in predicting the  $E_c$  value of RAC has been questioned (Xiao et al. 2006; Corinaldesi 2010). This is mainly because although the developed relationships may fit the researchers' own experimental data well, they cannot be used to predict the results of other researchers' due to the diverse nature of RA used in different studies.

The comparison between the modeling results of the above equations and the experimental test results are shown in Table 5-1 - Table 5-3, respectively.

**Table 5-1 - Modeling results of elastic modulus of Case I**

Mix	Experimental results		Modeling $E_c$ (GPa)				Relative error (%)			
	$f_{cu}$ (MPa)	$E_c$ (GPa)	Eq.(5-1)	Eq.(5-2)	Eq.(5-3)	Eq.(5-4)	Eq.(5-1)	Eq.(5-2)	Eq.(5-3)	Eq.(5-4)
Case I	69.6	32.3	31.51	38.85	47.21	34.55	2.44	20.28	46.17	24.77
	59.4	27.43	29.91	35.08	40.74	30.7	9.03	27.88	48.53	6.07
	69.8	27.26	31.54	38.93	47.34	34.63	15.71	42.8	73.66	19.1
	67.8	27.02	31.24	38.19	46.07	33.87	15.62	41.32	70.51	34.27
	68.7	26.85	31.38	38.52	46.64	34.21	16.86	43.46	73.72	21.27
	62.1	26.79	30.35	36.08	42.46	31.72	13.28	34.67	58.48	13.86
	75.3	36.1	32.34	40.96	50.83	36.71	10.41	13.47	40.8	5.39
	63	28.67	30.49	36.41	43.03	32.06	6.36	27	50.08	8.85
	76.3	30.9	32.48	41.33	51.46	37.08	5.12	33.76	66.55	20.92
	74.8	30.98	32.27	40.78	50.51	36.52	4.17	31.62	63.05	32.01
	72.7	30	31.97	40	49.18	35.72	6.56	33.33	63.94	35.14
	66.3	28.48	31.01	37.63	45.12	33.3	8.89	32.13	58.43	36.77
<b>Average</b>							9.54	31.81	59.49	21.54

**Table 5-2 - Modeling results of elastic modulus of Case II**

Mix	Experimental results		Modeling $E_c$ (GPa)				Relative error (%)			
	$f_{cu}$ (MPa)	$E_c$ (GPa)	Eq.(5-1)	Eq.(5-2)	Eq.(5-3)	Eq.(5-4)	Eq.(5-1)	Eq.(5-2)	Eq.(5-3)	Eq.(5-4)
Case II	34.5	25.1	25	25.87	24.95	21.28	0.41	3.05	0.62	39.11
	35	20.85	25.12	26.05	25.26	21.47	20.46	24.94	21.16	44.16
	29.2	21.9	23.66	23.9	21.58	19.28	8.03	9.15	1.45	30.28
	27.7	20.49	23.25	23.35	20.63	18.71	13.47	13.95	0.69	41.52
	48.3	30.68	27.93	30.97	33.7	26.5	8.95	0.95	9.85	26.08
	47.6	28.86	27.8	30.71	33.26	26.23	3.68	6.42	15.23	24.9
	42	24.46	26.67	28.64	29.7	24.12	9.05	17.09	21.44	8.92
	42.9	26.55	26.86	28.97	30.27	24.46	1.17	9.13	14.03	13.11
	61.6	32.36	30.27	35.89	42.14	31.53	6.47	10.91	30.22	16.54
	60	29.42	30.01	35.30	41.12	30.92	1.99	19.99	39.78	15.53
	53.7	24.61	28.93	32.97	37.13	28.54	17.54	33.97	50.86	5.61
	53.2	28.5	28.84	32.78	36.81	28.35	1.19	15.03	29.16	8.38
	80.5	35.43	33.06	42.89	54.13	38.67	6.68	21.04	52.78	109.15
	78.2	34.76	32.75	42.03	52.67	37.80	5.79	20.93	51.52	22.88
	71.2	29.52	31.75	39.44	48.23	35.16	7.55	33.62	63.38	22.82
	65.4	30.62	30.87	37.30	44.55	32.96	0.82	21.81	45.49	18.04

39.4	26.6	26.12	27.68	28.05	23.14	1.81	4.05	5.47	14.87
39.8	25.18	26.2	27.83	28.31	23.29	4.07	10.51	12.42	16.69
34	22.83	24.88	25.68	24.63	21.09	8.97	12.48	7.88	19.12
28.4	21.5	23.44	23.61	21.08	18.98	9.04	9.8	1.97	19.55
53	31.1	28.80	32.71	36.68	28.28	7.39	5.18	17.95	2.42
51.3	30.68	28.49	32.08	35.6	27.63	7.12	4.57	16.05	1.74
47	25.91	27.68	30.49	32.88	26.01	6.84	17.68	26.88	3.83
46.3	27.22	27.55	30.23	32.43	25.74	1.2	11.06	19.15	3.48
69.6	34.5	31.51	38.85	47.21	34.55	8.66	12.61	36.85	29.36
67.7	33.42	31.23	38.15	46.01	33.83	6.57	14.15	37.67	28.97
55.5	26.3	29.24	33.64	38.27	29.22	11.19	27.89	45.51	6.96
58.6	27.94	29.77	34.78	40.24	30.39	6.56	24.49	44.01	16.83
88.3	36.88	34.09	45.77	59.08	41.62	7.57	24.11	60.19	40.4
84.1	35.49	33.54	44.22	56.41	40.03	5.49	24.59	58.96	43.62
74.3	29.92	32.2	40.59	50.20	36.33	7.62	35.67	67.77	19.64
73.3	30.74	32.06	40.22	49.56	35.95	4.28	30.84	61.23	20.72
<b>Average</b>						6.8	16.61	30.24	22.98

**Table 5-3 - Modeling results of elastic modulus of Case III**

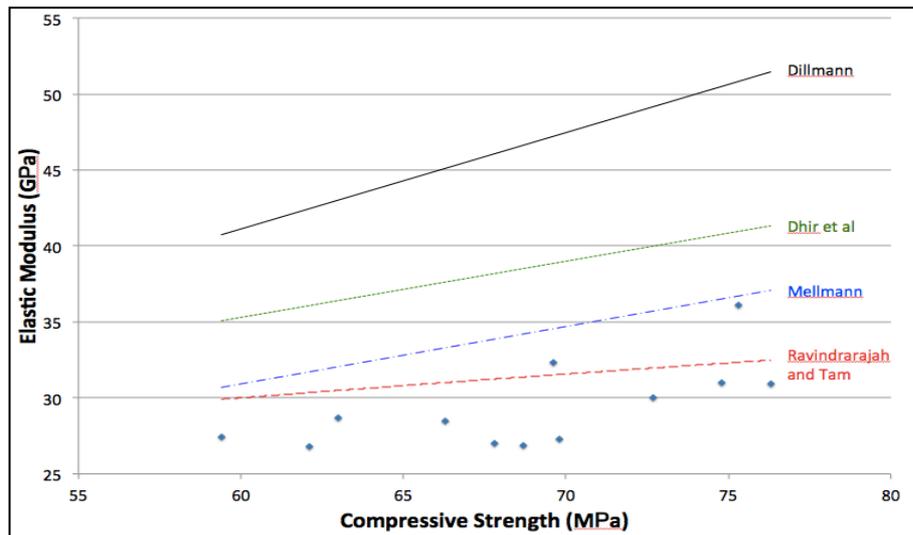
Mix	Experimental results		Modeling $E_c$ (GPa)				Relative error (%)			
	$f_{cu}(MPa)$	$E_c(GPa)$	Eq.(5-1)	Eq.(5-2)	Eq.(5-3)	Eq.(5-4)	Eq.(5-1)	Eq.(5-2)	Eq.(5-3)	Eq.(5-4)
	54.4	29.85	29.05	33.23	37.57	28.81	2.68	11.32	25.86	9.06
	54.4	28.42	29.05	33.23	37.57	28.81	2.22	16.92	32.2	7.51
	54.9	27.44	29.14	33.41	37.89	28.99	6.19	21.77	38.08	0.53
	52.5	27.09	28.71	32.53	36.37	28.09	5.99	20.06	34.24	0.03
	54.2	27.49	29.02	33.15	37.44	28.73	5.55	20.6	36.21	5.6
	52.3	25.46	28.68	32.45	36.24	28.01	12.63	27.46	42.33	0.15
	46.9	23.18	27.66	30.45	32.81	25.97	19.34	31.38	41.55	7.46
<b>Case III</b>	48.4	29.03	27.95	31.01	33.76	26.54	3.71	6.81	16.31	11.93
	44	27.1	27.09	29.38	30.97	24.87	0.05	8.41	14.29	11.17
	47.5	27	27.78	30.68	33.19	26.2	2.89	13.61	22.94	7.64
	42.4	26.69	26.76	28.79	29.96	24.27	0.25	7.86	12.24	13.42
	46.7	24.42	27.62	30.38	32.69	25.89	13.12	24.4	33.85	1
	41.1	24.15	26.48	28.31	29.13	23.78	9.67	17.21	20.63	7.46
	49.1	27.39	28.09	31.27	34.21	26.8	2.54	14.15	24.89	12.15
	44.7	25.69	27.23	29.64	31.42	25.14	5.99	15.37	22.29	3.94

50.7	26.72	28.38	31.86	35.22	27.41	6.23	19.23	31.82	5.48
39.9	24.55	26.23	27.86	28.37	23.32	6.83	13.49	15.57	9.07
48.2	30.45	27.91	30.93	33.64	26.46	8.33	1.59	10.47	24.3
50.3	29.58	28.31	31.71	34.97	27.26	4.29	7.2	18.22	10.46
49.2	26.78	28.1	31.3	34.27	26.84	4.94	16.89	27.97	3.81
60.5	31.51	30.09	35.49	41.44	31.11	4.51	12.62	31.52	98.73
59.9	30.94	29.99	35.26	41.06	30.88	3.07	13.97	32.71	99.82
60	29.14	30.01	35.3	41.12	30.92	2.97	21.14	41.12	106.12
57.6	28.08	29.6	34.41	39.6	30.01	5.43	22.55	41.03	106.89
59.4	30.27	29.91	35.08	40.74	30.7	1.2	15.88	34.6	101.4
57.6	28.05	29.6	34.41	39.6	30.01	5.54	22.68	41.18	107
54.8	24.24	29.12	33.38	37.82	28.96	20.14	37.69	56.04	119.46
54.1	30	29	33.12	37.38	28.69	3.34	10.39	24.6	95.64
45.9	27.9	27.47	30.08	32.18	25.59	1.55	7.82	15.33	91.73
54	28.26	28.98	33.08	37.32	28.65	2.55	17.06	32.05	101.39
45.4	27.85	27.37	29.9	31.86	25.4	1.73	7.35	14.4	91.21
50.5	26.14	28.35	31.79	35.1	27.33	8.44	21.6	34.26	104.56
42.1	25.58	26.7	28.68	29.77	24.16	4.36	12.11	16.37	94.43
54	30.13	28.98	33.08	37.32	28.65	3.81	9.79	23.85	95.1
47.4	26.15	27.76	30.64	33.13	26.16	6.16	17.16	26.69	100.04
52.8	28.87	28.77	32.64	36.56	28.2	0.36	13.04	26.62	97.68
42	25.55	26.67	28.64	29.7	24.12	4.4	12.09	16.26	94.4
51.3	33.86	28.49	32.08	35.6	27.63	15.85	5.25	5.15	81.61
53.6	30.35	28.91	32.93	37.06	28.5	4.75	8.51	22.12	93.91
51.3	27.86	28.49	32.08	35.6	27.63	2.28	15.15	27.8	99.19
<b>Average</b>						5.65	15.49	27.14	53.31

### 5.2.1 Modeling results of Case I

For recycled high strength concrete made with RAs produced from parent concrete of different qualities, the relationship between the tested and predicted  $E_c$ , at 28 and 90 days, and the corresponding tested  $f_{cu}$  values are shown in Figure 5-1. From the Figure, it can be noticed that apart from the equation established

by Sri Ravindrarajah and Tam (1985), the other three equations all overestimate the  $E_c$  values based on the tested  $f_{cu}$  values. When Equation 5-1 is adopted, the produced mean relative error, as shown in Table 5-1, reaches to about 9.54%.

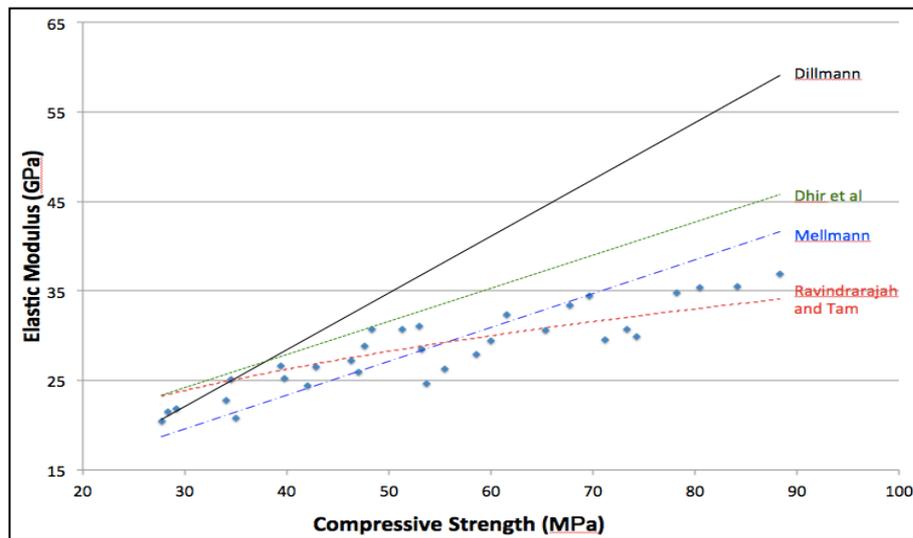


**Figure 5-1 - Modeling results using empirical equations in Case I**

The poor performance of the above relationships may be due to the following reasons: (1) a low water to cement ratio of only 0.35 is used in the production of RAC made with RAs of Case I; (2) crushed stone fines with a FM value of 3.28 is used in this study, while river sand is generally adopted by most of the studies of others; (3) some other parameters, for example, the cement type used in this study may be different from that of the references.

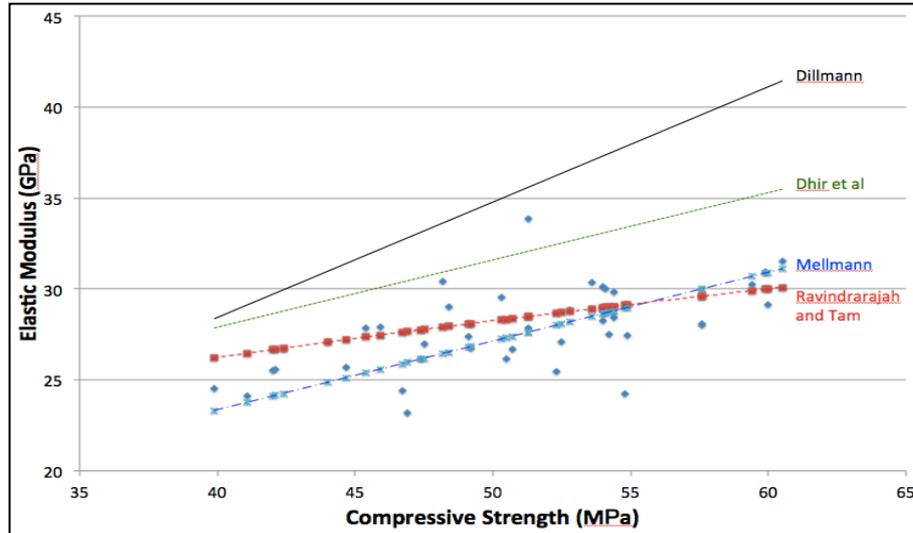
### 5.2.2 Modeling results of Case II

A comparison between the predicted  $E_c$  values by the empirical equations and the actual ones in RAC of Case II is shown in Figure 5-2. Relative to the modeling results in Case I, the performance of the empirical equations in Case II is slightly better. However, the equations established by Dillmann (1998) and Dhir et al. (1999) still overestimate the  $E_c$  values, and most of the predicted results produced by Equation 5-3 are not satisfactory.



**Figure 5-2 - Modeling results using empirical equations in Case II**

Similar to the modeling results of Case I, Equation 5-1 still has the best predictions, and the average relative error is only 6.8%. Besides, the errors of most of the predictions are lower than 10%.



**Figure 5-3 -Modeling results of empirical equations in Case III**

### 5.2.3 Modeling results of Case III

Figure 5-3 shows that the performance of each empirical equation in predicting the elastic modulus of RAC in Case III. Similarly, Eqs.(5-2- 5-4) cannot prove their applicability in modeling the  $E_c$  values of RAC made with RAs containing added masonries. But the predictions of Equation 5-1 can be nearly comparable with the actual tested values, and the average relative error the equation is only 5.65%.

Above all, most of the empirical equations proposed by one researcher cannot be used to predict the results of other researchers' due to the diverse nature of RAs and the variations of some other parameters used in different studies.

## 5.3 REGRESSION ANALYSIS BETWEEN RAC PROPERTIES AND AGGREGATE CHARACTERISTICS

### 5.3.1 Modeling elastic modulus using aggregate properties

The  $E_c$  of concrete is also a function of the modulus of elasticity of the aggregates and the cement matrix, and their relative proportions used in the concrete. It is well known that the  $E_c$  of the RA used in RAC vary greatly.

de Brito and Robles (2008) suggested that the  $E_c$  of RAC could be modeled by using the density or the  $W_a$  values of the mixed aggregates, as shown in Figure 5-4. Through the collation of a large number of data from different sources and regression analyses, they modeled the ratio between the 28d  $E_c$  of RAC and that of the corresponding normal aggregate concrete ( $E_{BR}/E_{BC}$ ) by correlation with the  $SG_{SSD}$  and the  $W_a$  values of the RA, respectively. The proposed relationships are as follow:

$$E_{BR}/E_{BC} = -2.1506(1 - D_{BR}/D_{BC}) + 1 \quad (5-5)$$

$$E_{BR}/E_{BC} = -0.0457(ab_{BR}/ab_{BC} - 1) + 1 \quad (5-6)$$

where  $BR$  and  $BC$  denote recycled aggregate and reference concrete, respectively;

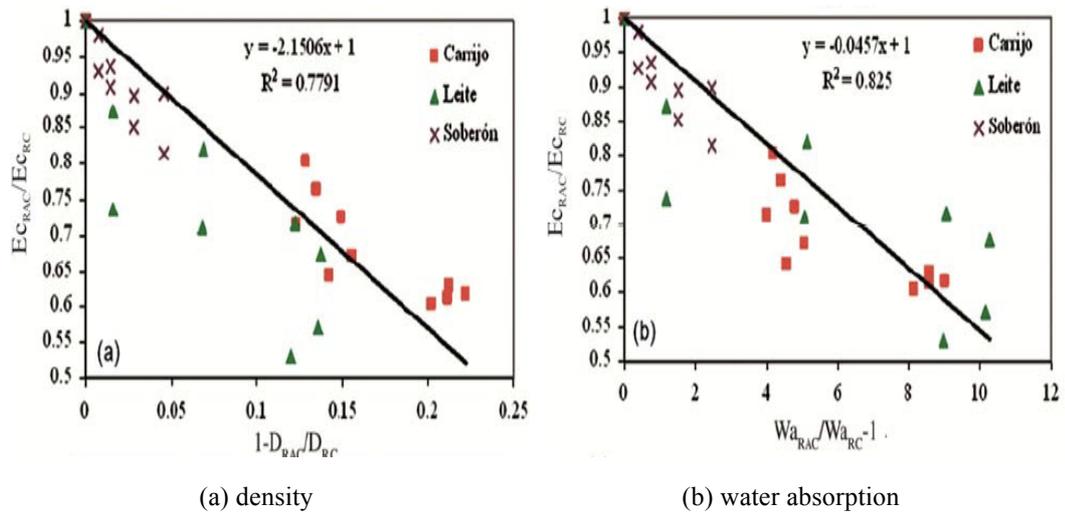
$D_{BR}$  and  $D_{BC}$  are the density of in *RAC* and the reference *NAC*, respectively;  $ab_{BR}$  and  $ab_{BC}$  are the water absorption of aggregates in *RAC* and the reference *NAC*, respectively.

The predicted  $E_c$  values of some of the testing sets by regression analysis (using Equations 5-5 and 5-6) are listed in Table 5-4, and they are also compared with the actual test values. The application of Equation 5-5 and Equation 5-6 in all the three Cases using the author's data are also shown in Figures 6-5 (a) and (b), respectively. From the Figure, it can be noticed that large discrepancy is resulted by using the two equations to predict the  $E_c$  of *RAC* made with the added masonry. This is mainly attributed to the lower density and higher absorption values of the masonry (crushed bricks and tiles), when compared with those of recycled concrete aggregate.

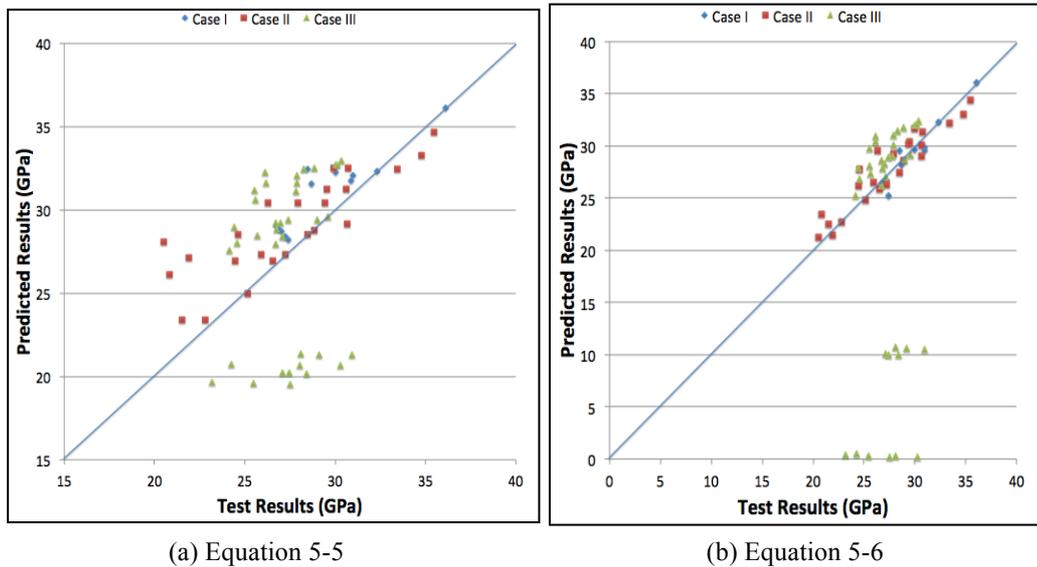
**Table 5-4 - Modeling results of elastic modulus by using Eqs.(5-5) and (5-6)**

Mix	Tested $E_c(GPa)$	Predicted		Relative		Mix	Tested $E_c(GPa)$	Predicted		Relative	
		$E_c(GPa)$		error (%)				$E_c(GPa)$		error (%)	
		Eq.(5-5)	Eq.(5-6)	Eq.(5-5)	Eq.(5-6)			Eq.(5-5)	Eq.(5-6)	Eq.(5-5)	Eq.(5-6)
Case I	27.43	28.23	25.21	2.93	21.4	Case III	28.42	20.17	9.95	29.01	64.98
	27.26	28.39	26.7	4.13	25.83		27.44	20.21	10.03	26.35	63.44
	27.02	28.7	26.46	6.24	30.64		27.09	20.24	10.11	25.28	62.7
	26.85	28.86	26.52	7.49	35.2		27.49	19.56	0.2	28.84	99.26
	26.79	29.02	26.44	8.32	39.23		25.46	19.6	0.33	23	98.7
	28.67	31.55	28.18	10.06	1.71		23.18	19.64	0.45	15.27	98.06
	30.9	31.73	29.84	2.67	3.43		29.58	29.61	29.13	0.09	1.53

	30.98	32.08	29.57	3.56	4.54	26.78	28.82	27.89	7.61	4.15
	30	32.26	29.64	7.52	1.19	29.03	29.4	28.7	1.29	1.14
	28.48	32.43	29.55	13.88	3.76	27.1	28.41	27.03	4.82	0.26
<b>Ave.</b>				6.68	16.69	27	29.2	28.26	8.14	4.66
						26.69	27.98	26.13	4.84	2.09
	20.85	26.1	23.39	25.18	12.19	24.42	28.99	27.81	18.7	13.9
	21.9	27.1	21.43	23.74	2.13	24.15	27.55	25.21	14.06	4.41
	20.49	28.1	21.22	37.14	3.56	27.39	29.42	28.86	7.4	5.36
	28.86	28.78	28.58	0.27	0.98	25.69	28.43	27.34	10.66	6.4
	24.46	26.94	26.16	10.16	6.97	26.72	29.22	28.58	9.37	6.97
	26.55	26.94	25.9	1.49	2.45	24.55	28.03	26.76	14.18	9.01
	29.42	30.41	30.19	3.36	2.63	30.94	21.3	10.51	31.17	66.04
	24.61	28.52	27.71	15.9	12.61	29.14	21.33	10.59	26.79	63.66
	28.5	28.52	27.44	0.08	3.72	28.08	21.37	10.67	23.91	62.01
	34.76	33.29	33.06	4.23	4.9	30.27	20.65	0.22	31.78	99.29
	29.52	31.25	30.37	5.87	2.87	28.05	20.69	0.35	26.23	98.75
<b>Case</b>	30.62	31.25	30.07	2.04	1.81	24.24	20.73	0.47	14.47	98.04
<b>II</b>	25.18	24.97	24.79	0.84	1.55	30.35	32.92	32.39	8.47	6.72
	22.83	23.39	22.72	2.45	0.5	27.86	32.04	31.02	15.02	11.33
	21.5	23.39	22.49	8.79	4.6	30	32.7	31.91	8.99	6.37
	30.68	29.18	28.97	4.9	5.58	27.9	31.59	30.06	13.22	7.73
	25.91	27.31	26.52	5.42	2.36	28.26	32.47	31.42	14.88	11.19
	27.22	27.31	26.25	0.34	3.55	27.85	31.11	29.06	11.72	4.34
	33.42	32.42	32.19	2.99	3.68	26.14	32.23	30.93	23.31	18.32
	26.3	30.41	29.55	15.62	12.34	25.58	30.63	28.04	19.74	9.61
	27.94	30.41	29.26	8.83	4.71	30.13	32.71	32.09	8.57	6.5
	35.49	34.65	34.41	2.36	3.04	26.15	31.61	30.4	20.89	16.24
	29.92	32.53	31.61	8.73	5.65	28.87	32.5	31.78	12.56	10.09
	30.74	32.52	31.3	5.81	1.81	25.55	31.17	29.76	21.99	16.47
<b>Ave.</b>				8.19	4.42	<b>Ave.</b>			16.18	32.21



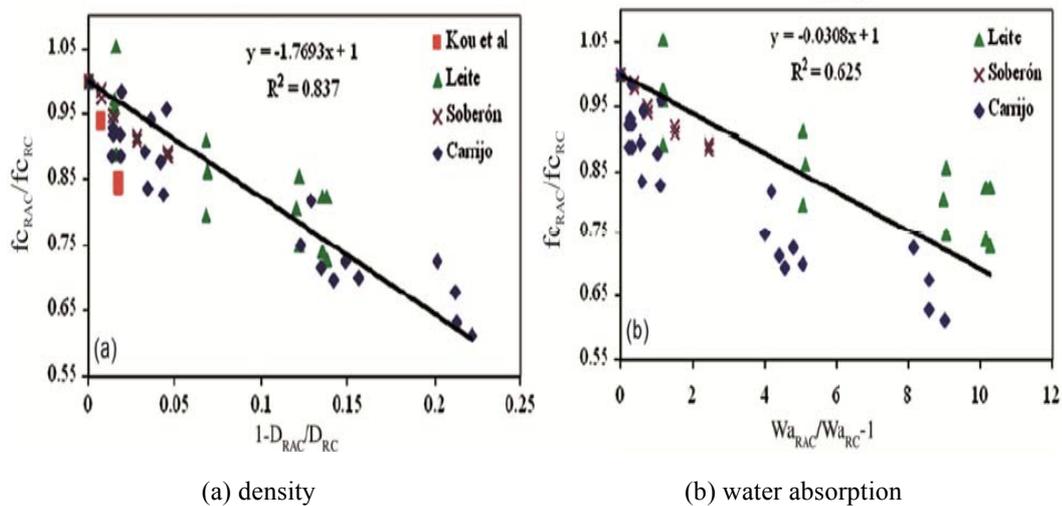
**Figure 5-4 - Relationship between elastic modulus and aggregate performance (de Brito and Robles 2008)**



**Figure 5-5 - The performance of Eq.(5-5) and Eq.(5-6) in modeling the elastic modulus of our data**

As shown in Table 5-4, the performance of Eq.(5-5) and Eq.(5-6) in modeling the  $E_c$  of Case I and Case II is also unstable. Good predictions can only be obtained when Equation 5-5, using the specific gravity of aggregate as a parameter, is applied to Case I with the mean relative error about 6.68%.

However, the error increases to about 8.19% when the relationship is used to predict the  $E_c$  values of Case II (with some prediction errors exceeding 25%). As regards Equation 5-6, the performance is just opposite. Although its mean error is only about 4.42% in modeling the  $E_c$  of Case II, its performance in Case I is poor, with an average relative error of 16.69%.



**Figure 5-6 - Relationship between compressive strength and aggregate performance (de Brito and Robles 2008)**

### 5.3.2 Modeling compressive strength using aggregate properties

Besides  $E_c$ , the  $f_{cu}$  of RAC can also be predicted by established relationships, as shown in Figure 5-6, by de Brito and Robles (2008) based on the specific gravity and the water absorption values of the RA. The established relationships are as follows:

$$f_{cBR}/f_{cBC} = -1.7693 (1 - D_{BR}/D_{BC}) + 1 \quad (5-7)$$

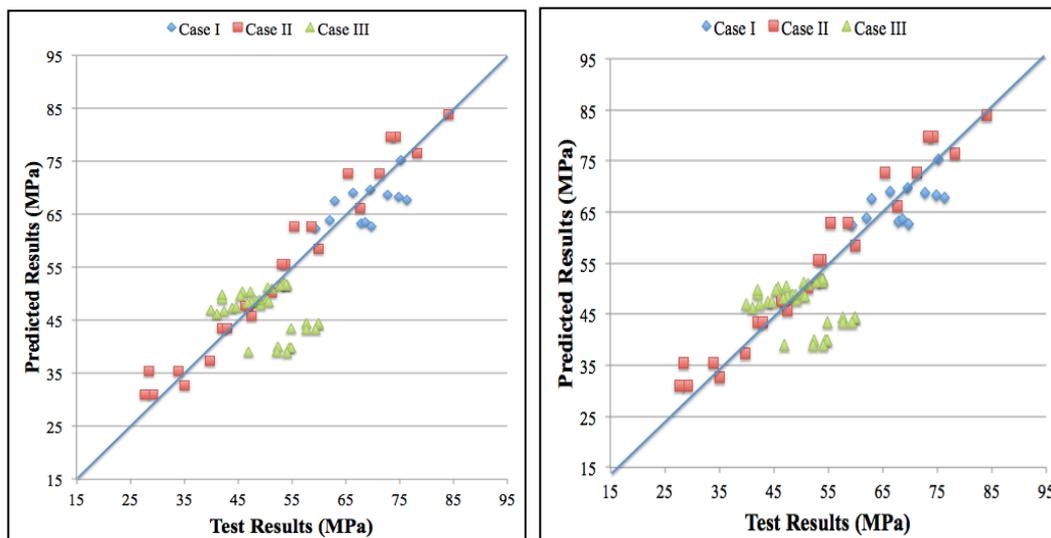
$$f_{cBR}/f_{cBC} = -0.0308 (ab_{BR}/ab_{BC} - 1) + 1 \quad (5-8)$$

where  $BR$  and  $BC$  denote recycled aggregate and reference concrete, respectively;

$D_{BR}$  and  $D_{BC}$  are the density of in  $RAC$  and the reference  $NAC$ , respectively;  $ab_{BR}$

and  $ab_{BC}$  are the water absorption of aggregates in  $RAC$  and the reference  $NAC$ ,

respectively.



(a) Equation 5-5

(b) Equation 5-6

**Figure 5-7 - Performance of Eq.(5-7) and Eq.(5-8) in modeling the compressive strength of our data**

Based on the three Cases, the comparison between the actual tested  $f_{cu}$  values and

the predicted ones produced by Eq.(5-7) and Eq.(5-8) is listed in Table 5-5.

Figure 5-7 gives the modeling results of Case I - Case III by Eq.(5-7) and Eq.(5-8). Similarly, the established relationships also perform poorly in modeling the  $f_{cu}$  of RAC made with the added masonries as RA. Noticeably, both equations can produce good predictions when they are applied to Cases I-II. The average relative errors of Eq.(5-7) and Eq.(5-8) in predicting the  $f_{cu}$  of Case I are about 6.87% and 7%, respectively. The errors can be further reduced to only 5.83% and 5.54%, respectively, when the two Equations are used to model the  $f_{cu}$  values of Case II.

Above all, there are limitations on using the relationships based on the SG and  $W_a$  values of RA in modeling the  $f_{cu}$  or  $E_c$  of RAC.

**Table 5-5 - Modeling results of the compressive strength by using Eq.(5-7) & Eq.(5-8)**

Mix	Tested $f_{cu}$ (MPa)	Predicted $f_{cu}$ (MPa)		Relative error (%)		Mix	Tested $f_{cu}$ (MPa)	Predicted $f_{cu}$ (MPa)		Relative error (%)	
		Eq.(5-7)	Eq.(5-8)	Eq.(5-7) )	Eq.(5-8) )			Eq.(5-7)	Eq.(5-8)	Eq.(5-7) )	Eq.(5-8) )
Case I	59.4	62.39	59.31	5.03	0.15	Case III	54.4	39.89	29.96	26.67	44.92
	69.8	62.66	61.47	10.23	11.94		54.9	39.94	30.06	27.24	45.25
	67.8	63.23	61.12	6.75	9.85		52.5	39.99	30.15	23.82	42.57
	68.7	63.5	61.21	7.56	10.9		54.2	38.98	17.99	28.09	66.81
	62.1	63.79	61.09	2.71	1.63		52.3	39.04	18.14	25.36	65.31
	63	67.5	64.17	7.14	1.85		46.9	39.09	18.29	16.65	61
	76.3	67.79	66.5	11.15	12.84		50.3	49.06	48.73	2.47	3.12
	74.8	68.4	66.13	8.55	11.6		49.2	47.98	47.36	2.47	3.74
72.7	68.7	66.22	5.5	8.91	48.4	48.78	48.25	0.79	0.3		

	66.3	69.01	66.09	4.09	0.31		44	47.43	46.4	7.79	5.45
<b>Ave.</b>				6.87	7		47.5	48.5	47.77	2.11	0.56
							42.4	46.85	45.4	10.5	7.08
	35	32.76	32.92	6.4	5.95		46.7	48.22	47.27	3.25	1.22
	29.2	31.07	31.1	6.42	6.52		41.1	46.26	44.38	12.56	7.99
	27.7	31.07	30.91	12.18	11.57		49.1	48.8	48.43	0.61	1.36
	47.6	45.84	46.07	3.69	3.22		44.7	47.46	46.74	6.17	4.56
	42	43.46	43.51	3.48	3.59		50.7	48.54	48.12	4.27	5.08
	42.9	43.46	43.23	1.31	0.76		39.9	46.92	46.1	17.59	15.54
	60	58.54	58.82	2.43	1.97		59.9	44.37	33.32	25.93	44.37
	53.7	55.59	55.64	3.52	3.61		60	44.42	33.43	25.96	44.28
	53.2	55.59	55.29	4.49	3.93		57.6	44.48	33.53	22.78	41.79
	78.2	76.5	76.87	2.17	1.7		59.4	43.35	20	27.03	66.32
	71.2	72.69	72.75	2.09	2.18		57.6	43.41	20.18	24.63	64.97
<b>Case</b>	65.4	72.68	72.29	11.13	10.53		54.8	43.48	20.34	20.66	62.88
<b>II</b>	39.8	37.41	37.59	6	5.54		53.6	52.08	51.74	2.83	3.47
	34	35.49	35.52	4.37	4.48		51.3	50.95	50.28	0.69	1.98
	28.4	35.49	35.3	24.95	24.28		54.1	51.79	51.23	4.26	5.3
	51.3	50.3	50.55	1.94	1.46		45.9	50.36	49.26	9.71	7.33
	47	47.69	47.74	1.47	1.58		54	51.5	50.72	4.64	6.08
	46.3	47.69	47.43	3.01	2.45		45.4	49.74	48.21	9.57	6.18
	67.7	66.15	66.46	2.29	1.83		50.5	51.19	50.19	1.37	0.62
	55.5	62.81	62.86	13.17	13.27		42.1	49.12	47.12	16.67	11.93
	58.6	62.81	62.47	7.18	6.6		54	51.81	51.42	4.05	4.78
	84.1	83.91	84.32	0.22	0.26		47.4	50.39	49.63	6.31	4.7
	74.3	79.73	79.8	7.31	7.4		52.8	51.53	51.1	2.4	3.23
	73.3	79.72	79.29	8.76	8.17		42	49.82	48.95	18.61	16.54
<b>Ave.</b>				5.83	5.54	<b>Ave.</b>				12.4	21.63

## 5.4 SUMMARY

This chapter presents the comparison of the experimental test results of  $E_c$  and  $f_{cu}$  of RAC made with RAs from different sources with the predicted results using

some established empirical relationships and regression analysis. The following conclusions can be drawn:

- Due to the diverse nature of RAs and different parameters that might have been considered in different previous studies, the empirical equations, which express the  $E_c$  as functions of the corresponding  $f_{cu}$ , cannot be used for RAC.
- For the relationships proposed by de Brito and Robles which model the  $f_{cu}$  or  $E_c$  of RAC by making reference to two RA characteristics (density and water absorption), the accuracy is limited. Also their uses require prior knowledge of information related to the reference normal concrete.

# **CHAPTER 6: FEASIBILITY STUDY ON THE USE OF ANN IN RAC**

## **6.1 INTRODUCTION**

In Chapter 2, the detailed basic knowledge of ANN and its application in concrete has been provided. It can be noticed that, although ANN has been widely adopted in many areas of normal concrete, such as properties prediction and mix design, currently it is mainly used in concrete made only with NA, and is rarely adopted in the concrete containing RA due to the complex composition of such aggregates. It is of interest to study whether ANN can be used in concrete made with RA as well.

In this chapter, several groups of RAC data sets including 28d  $f_{cu}$  and  $E_c$  values, collected from 5 different literatures (Koulouris 2005; Kou 2006; Dhir and Paine 2007; Guan 2011; Kotrayothar 2012), are used as the sample data sets to construct respective ANN models according to the method described in Section 2.4.3. The above literatures are selected mainly due to that these literatures contain large amounts of experimental data related to the RAC properties,

respectively, which are conducive to be used to conduct ANN models. For ease of expression, data from the above literatures are designated as K05, K06, D07, G11 and K12, respectively.

In the first part, each model is constructed to predict the  $E_c$  of RAC based on the given  $f_{cu}$  values. While in the last two parts, the  $E_c$  and  $f_{cu}$  values of RAC are modeled, respectively, by using the mix proportions as input variables. The main objectives of this chapter are as follows:

- To examine whether ANN is suitable for use in modeling the properties of RAC according to the traditional methods,
- To explore the difference between the use of ANN in NAC and RAC,
- To indicate the problems that need to be resolved to provide the constructed ANN model in RAC with generalization capacity.

For each model, the dataset is randomly divided into three groups, acting as the training set, validation set and testing set, respectively. To provide the reliability of the modeling results, the ratio of the latter two sets to the total dataset is no less than 25%. The indexes like MAPE,  $R^2$  and RMS are used to assess the performance of networks.

## 6.2 MODELING THE ELASTIC MODULUS OF RAC BY USING THE CORRESPONDING COMPRESSIVE STRENGTH VALUES

Various correlation relationships, including design codes and empirical equations, usually express  $E_c$  as a function of  $f_{cu}$ . Similarly, by using ANN,  $E_c$  can also be modeled with only  $f_{cu}$  values as input variable.

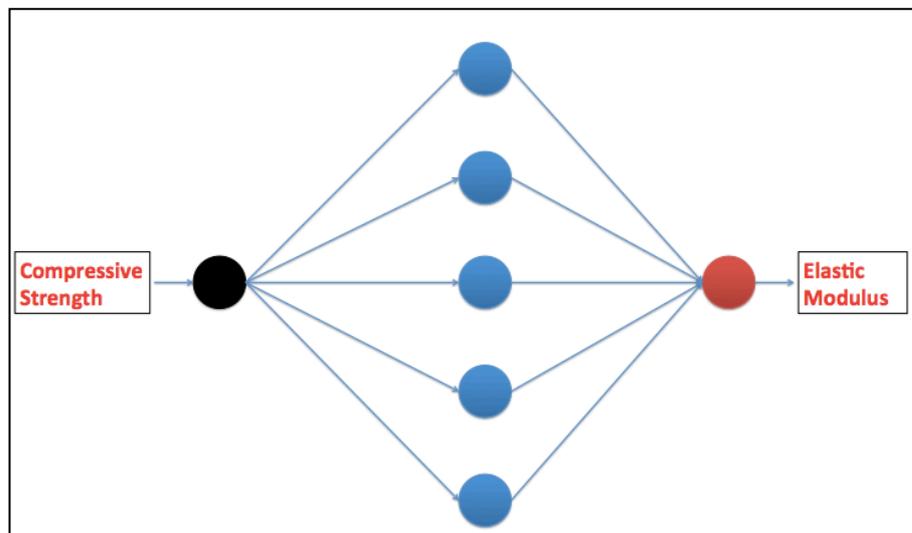


Figure 6-1 - ANN model for  $E_c$  with the  $f_{cu}$  as input variable

As shown in Figure 6-1, there are 3 layers in the constructed ANN model, with 1 neuron in the input layer, 5 neurons in the hidden layer and 1 neuron in the output layer. The network architecture and parameters selected are as follows:

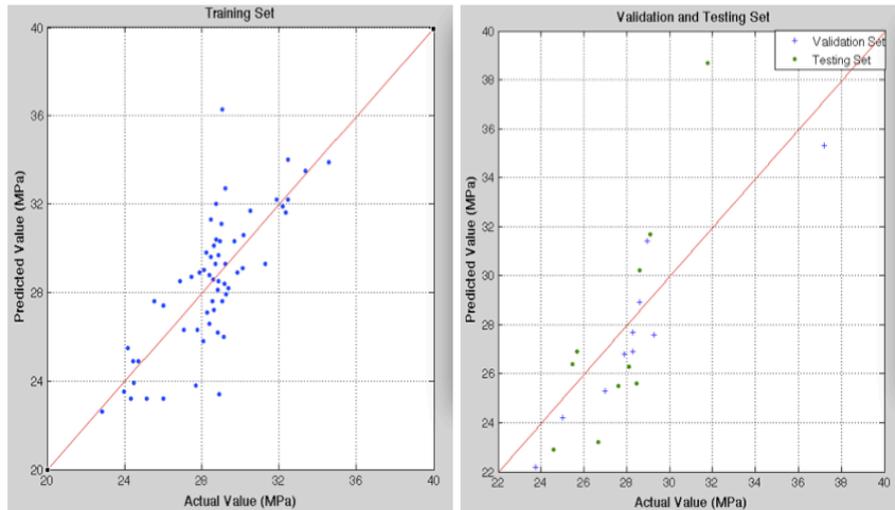
- Number of input layer units = 1
- Number of hidden layers = 1

- Number of hidden layer units = 5
- Number of output layer units = 1
- Momentum rate = 0.9
- Learning rate = 0.01
- Learning cycle=1000

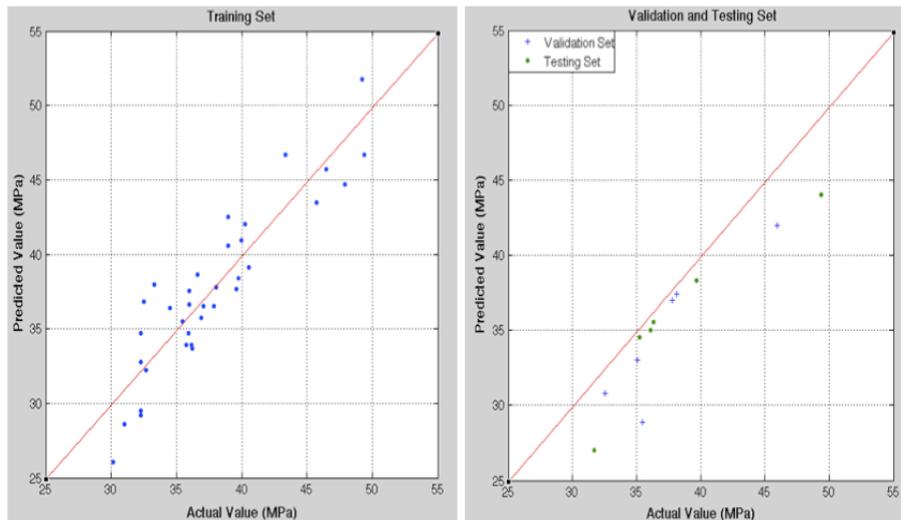
**Table 6-1 - Performance of networks with compressive strength as input variable**

Sets	Index	K06	K12	K05	G11	D07
Total No.		80	47	30	39	94
<b>Training</b>	Number	60	35	22	29	70
	R <sup>2</sup>	0.9955	0.9963	0.9937	0.9974	0.9973
	MAPE (%)	5.13	5.43	8.08	4.09	3.8
	RMS	1.9295	2.3034	1.5953	1.6025	1.2651
<b>Testing</b>	Number	10	6	4	5	12
	R <sup>2</sup>	0.9885	0.9929	0.987	0.9984	0.9979
	MAPE (%)	8.81	6.76	10.44	3.74	3.56
	RMS	3.0088	3.0337	2.4833	1.2574	1.0888
<b>Validation</b>	Number	10	6	4	5	12
	R <sup>2</sup>	0.9972	0.9909	0.9979	0.9984	0.9907
	MAPE (%)	4.85	8.07	5.94	3.38	7.14
	RMS	1.4757	3.3592	1.1333	1.2287	2.2396

The detailed performance of all constructed ANN models, reflected by R<sup>2</sup>, RMS and MAPE, are shown in Table 6-1. Figures 6-2- 6-6 also show the performance of ANN using the respective data sources.



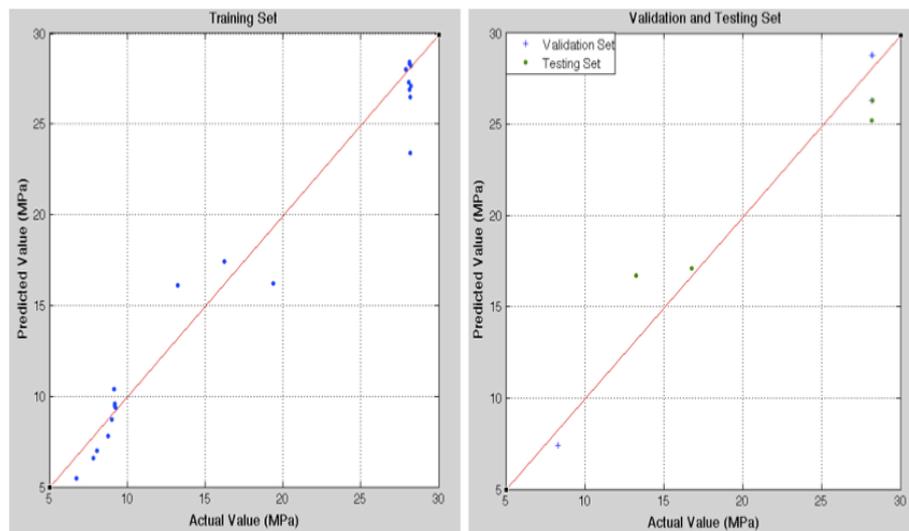
**Figure 6-2 - A comparison between the predicted values and the tested ones of K06**



**Figure 6-3 - A comparison between the predicted values and the tested ones of K12**

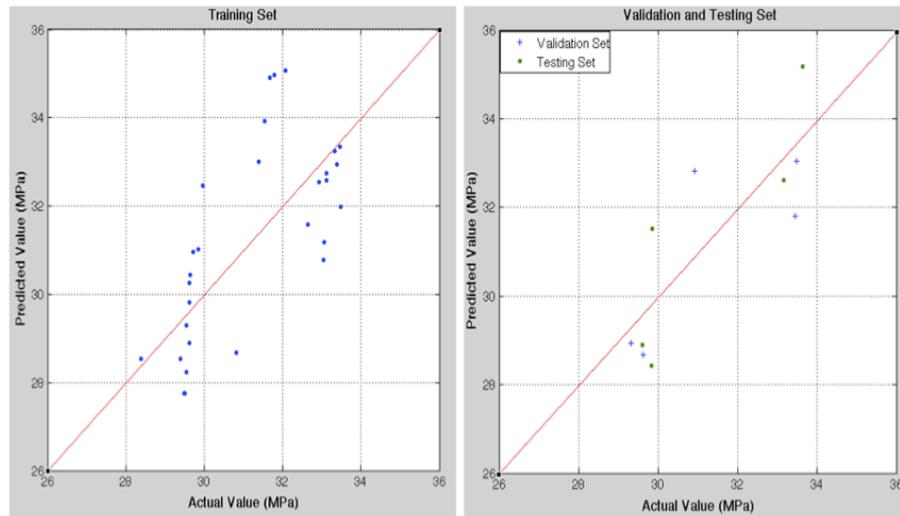
The approximation capability of ANN is proved, as shown in Table 6-1, with  $R^2$  in the training set of each source over 0.993, and it may even close to 1 if appropriate hidden layers and neurons are selected. However, its performance in the testing and validation sets is not as well: for the dataset of Koulouries (K05), the MAPE index in the testing set exceeds 10%. The poor performance may be

attributed to the factors affecting the  $f_{cu}$  and  $E_c$  of RAC may be not the same. Obviously, such high error in modeling the researchers' respective datasets infers the models would be more unreliable if used to predict the data sets of other researchers.

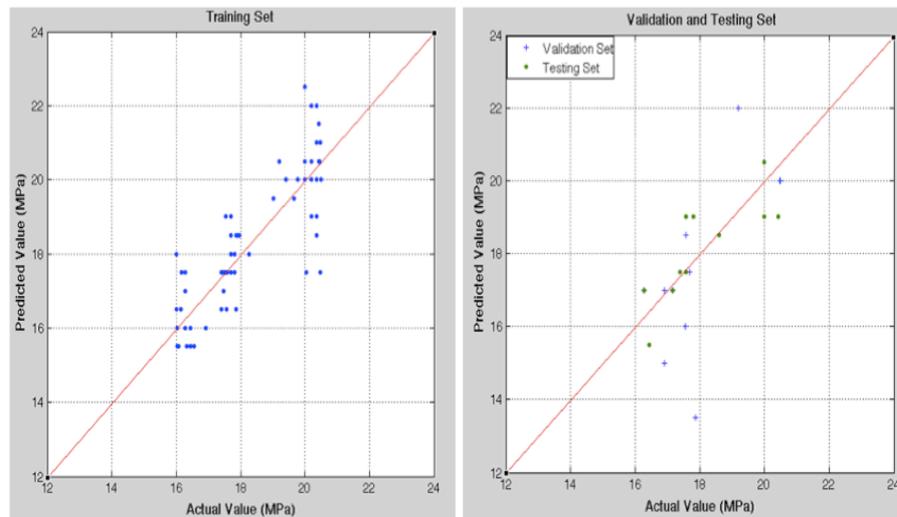


**Figure 6-4 - A comparison between the predicted values and the tested ones of K05**

This can be also used to explain why some established regression relationships are unable to be generally applied, since good performance in the training set does not necessary imply similar performance in the testing set, especially in the case that the datasets adopted for verifying the relationships are collected from unrelated sources. Therefore, for the better prediction of the properties of RAC, it is necessary to use more factors, such as concrete mixes and aggregate characteristics, as the input variables to establish the ANN model.



**Figure 6-5 - A comparison between the predicted values and the tested ones of G11**



**Figure 6-6 - A comparison between the predicted values and the tested ones of D07**

### **6.3 MODELING THE ELASTIC MODULUS OF RAC BY USING THE MIXS AND AGGREGATE CHARACTERISTICS**

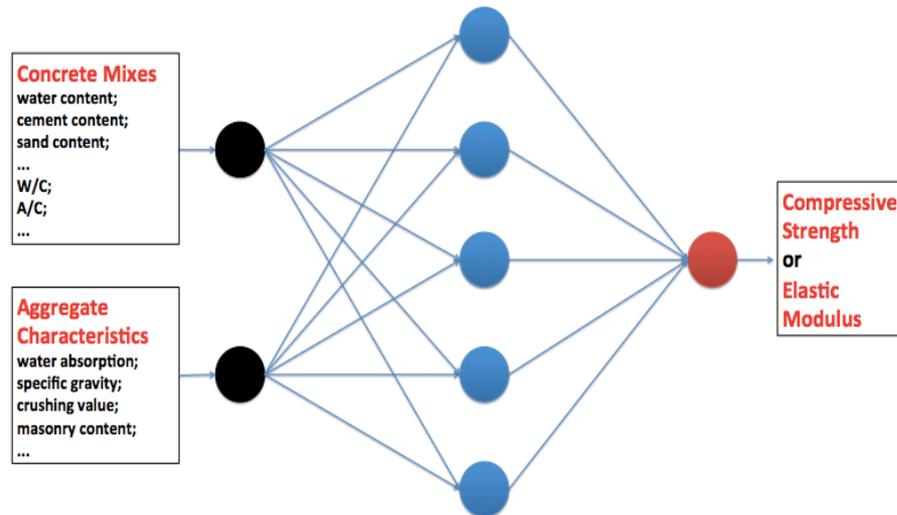
In this section, the datasets used are the same as in Section 6.2, but more factors that may affect the  $E_c$  of RAC, such as concrete mix proportions and aggregate characteristics, are used as the inputs of each of the model, as shown in Figure

6-7. Table 6-2 lists some details of each dataset.

**Table 6-2 - Details of each dataset**

<b>Source</b>	<b>K06</b>	<b>K12</b>	<b>K05</b>	<b>G11</b>	<b>D07</b>
<b>Concrete Mixes</b>					
W-kg/m <sup>3</sup>	160-225	120-240	165-186	225	180-190
C-kg/m <sup>3</sup>	260-410	300-600	180-411	385-750	214-311
S-kg/m <sup>3</sup>	582-729	720	465-835	562-835	614-853
NA-kg/m <sup>3</sup>	0-1140	0-1080	0-1270	0-940	0-1168
RA-kg/m <sup>3</sup>	0-1107	0-1080	0-1260	0-840	0-1156
FA-kg/m <sup>3</sup>	0-143.5	/	/	/	/
w/b	0.32-0.55	0.3-0.6	0.4-1.03	0.3-0.58	0.61-0.84
A/b	3.02-4.67	3-6	4.14-10.98	1.75-4.61	5.11-9.17
s <sub>p</sub>	0.37-0.41	0.4	0.27-0.43	0.4-0.5	0.39-0.43
r(RA/NA)-%	0-100	0-100	0-100	0-100	0-100
r(FA/b)-%	0-0.35	/	/	/	/
<b>Characteristics of recycled aggregates</b>					
W <sub>a</sub> -(%)	3.77	2.68	5.2	4.34-5.96	3.5-28
SG <sub>SSD</sub> -(g/cm <sup>3</sup> )	2.53	2.52	2.375	2.36-2.46	1.94-2.65
ACV-(%)	/	22.31	/	21.7-25	/
TFV-(KN)	126	/	/	/	/
AIV-(%)	/	/	/	/	13-27
LAV-(%)	/	/	/	32.9-38.6	29-60
Brick-(%)	/	/	3.17	/	0-100
Impurity-(%)	/	/	4.1	/	0-0.7
<b>Some other parameters</b>					
NA type	Crushed granite	/	Un-crushed gravel	Crushed granite/	
Cement type	OPC52.5	OPC	OPC	OPC 42.5N	/
Aggregate moisture	air-dried	SSD	air-dried	/	/
FM of Sand	2.11	/	/	/	/
Crushing method	plant	plant	/	plant	/
<b>Hardened Properties</b>					
f <sub>c</sub> -(MPa)	25.2-76.7	25.3-80.4	7.7-38.7	34.3-82.6	10-39.5
E <sub>c</sub> -(GPa)	22.2-38.7	26.1-51.8	5.5-28.8	27.8-35.2	13.5-22.5

/ represents the feature of the 1<sup>st</sup> column is not used or introduced in the collected dataset.



**Figure 6-7 - ANN models with the concrete mixes and aggregate characteristics as input variables**

For K06, crushed granite, river sand and OPC 52.5 were used to prepare NAC, with water-cement ratios ranged from 0.4 to 0.55. RA from a recycling plant was used to replace coarse aggregate by 0, 20, 50 and 100%, respectively, and Class F fly ash was adopted as a partial replacement or addition of cement in some mixes. Both standard water curing and steam curing were adopted. The maximum particle size of the coarse aggregate was 20 mm, and the use of RA was at an air-dried state. So the selected input variables for building the ANN model are the amounts (kg) of water, cement, fly ash, sand, NA and RA used in 1 m<sup>3</sup> of concrete mixture, water to binder ratio, aggregate to binder ratio, the percentage of sand in the total aggregate, the replacement ratio of NA by RA, the ratio of fly ash to the total binder used and the curing method.

For the dataset of K12, the amount of sand used in all the mixes was kept constant at  $720 \text{ kg/m}^3$ , RA with a maximum particle size of 20mm was used at a saturated surface dried condition, and OPC was adopted. The main parameters considered in this study were the RA replacement ratios, water to cement ratios and aggregate to cement ratios, which were in the ranges of 0-100 %, 0.35-0.6 and 3-6, respectively. Therefore, only seven factors are selected as the inputs of the constructed ANN model, and they are: the amount (kg) of water, cement, NA and RA used water to cement ratio, aggregate to cement ratio, and the replacement ratio of NA by RA.

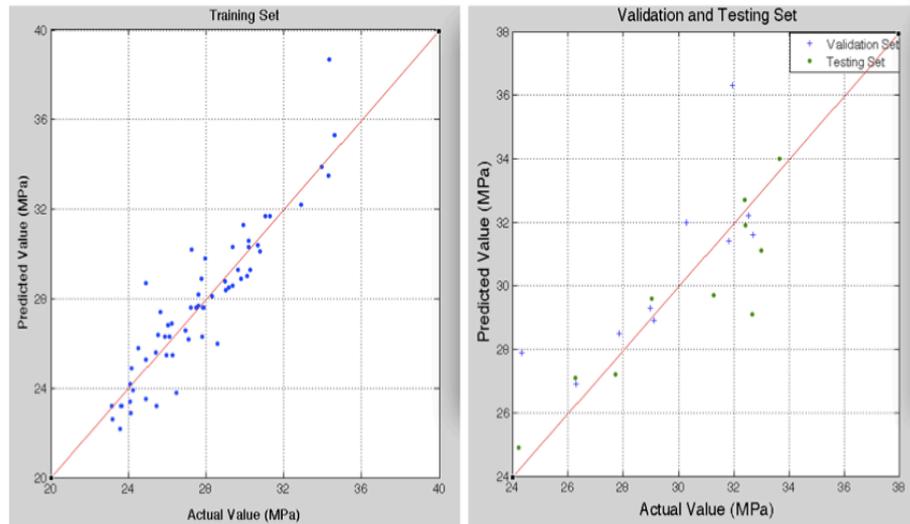
For the dataset of K05, OPC - CEM I 42.5 N was used, un-crushed Thames valley gravel (5-20 mm) was used as the NA, RA, derived from C&D debris, was adopted to replace the NA by 0, 30, 50, 70 and 100%, respectively. Besides, air-entrainment was also adopted in some mixes. The corresponding water to cement ratios varied between 0.4 and 1.03. The inputs of ANN model for this dataset are: the quantity (kg) of water, cement, sand, NA and RA used, water to cement ratio, aggregate to cement ratio, the replacement ratio of NA by RA and whether or not the air-entrainment agent is added.

**Table 6-3 - Networks performance with mixes and aggregate characteristics as input variables**

<b>Sets</b>	<b>Index</b>	<b>Kou</b>	<b>Kotrayothar</b>	<b>Koulouries</b>	<b>Guan</b>	<b>Dhir and Paine</b>
Total No.		80	47	30	39	94
<b>Training</b>	Number	60	35	22	29	70
	R <sup>2</sup>	0.998	0.9983	0.9979	0.9994	0.9988
	MAPE (%)	3.26	3.19	5.53	2.1	2.84
	RMS	1.2585	1.5223	0.898	0.7736	0.8376
<b>Testing</b>	Number	10	6	4	5	12
	R <sup>2</sup>	0.9976	0.9993	0.9994	0.9989	0.9983
	MAPE (%)	3.7	2.05	2.98	3.28	3.8
	RMS	1.453	1.0054	0.5711	1.0761	1.0029
<b>Validation</b>	Number	10	6	4	5	12
	R <sup>2</sup>	0.996	0.9995	0.9985	0.9992	0.9966
	MAPE (%)	4.25	2	5.98	2.08	4.9
	RMS	1.9264	0.835	0.9504	0.8866	1.4285

For the dataset of G11, concrete of three grades were designed with water to cement ratios of 0.3, 0.375 and 0.584, respectively. OPC - CEM I 42.5N, river sand and crushed granite were used. Besides, RA of 5-20 mm collected from four recycling plants was used to substitute crushed granite at 0, 20, 50 and 100% levels. As the amounts of water in all the mixes were kept at 225 kg/m<sup>3</sup>, the following inputs are adopted for the construction of the ANN model: the amounts (kg) of cement, sand, NA and RA used, water to cement ratio, aggregate to cement ratio, sand percentage in the total aggregate, replacement ratios of NA by RA and aggregate characteristics, such as  $W_a$ ,  $SG_{SSD}$ , LAAV and ACV. The use of many aggregate characteristics as inputs is to better represent the

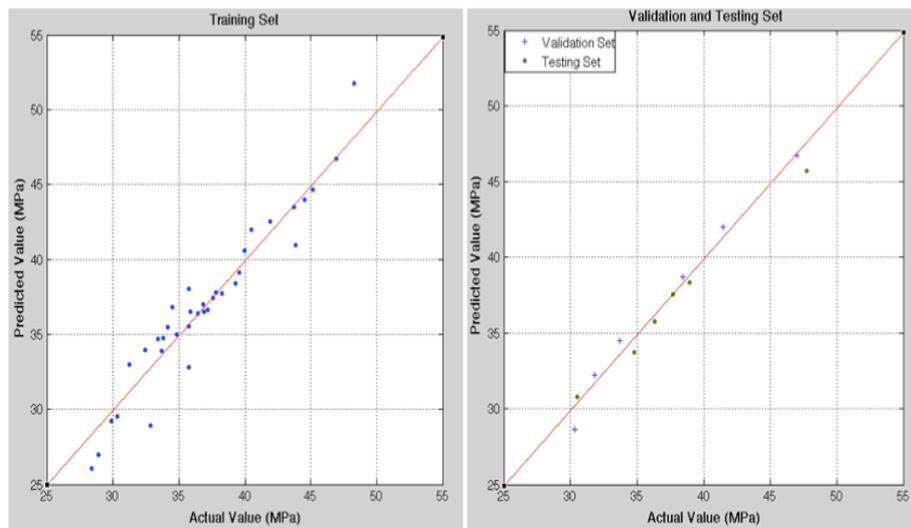
properties of different aggregates.



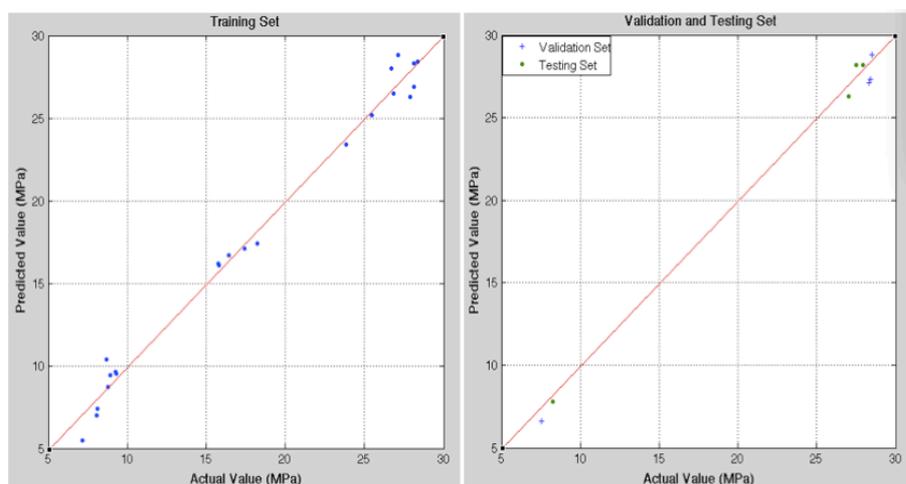
**Figure 6-8 - A comparison between the predicted values and the tested ones of K06**

For the dataset of D07, the properties of cement, sand and NA were not introduced in detail. Many types of RA were used including three types of crushed old concrete, three types of crushed bricks, eight combinations of crushed bricks and crushed concrete, and three commercially sourced RAs. Two W/C ratios were used: 0.61 and 0.84. Besides, many replacement ratios of NA by RA were also examined. The input variables selected for the ANN model are the amounts of cement, sand, NA and RA used, W/C ratio, aggregate to cement ratio, sand percentage to the total aggregate, replacement ratios of NA by RA and aggregate characteristics, such as  $W_a$ ,  $SG_{SSD}$ , LAAV, AIV, brick and impurity contents.

The performance of all the constructed ANN models, as reflected by indexes such as  $R^2$ , RMS and MAPE, are shown in Table 6-3. Figures 6-8-6-12 also show the performance of each model in the training, validation and testing sets, respectively.

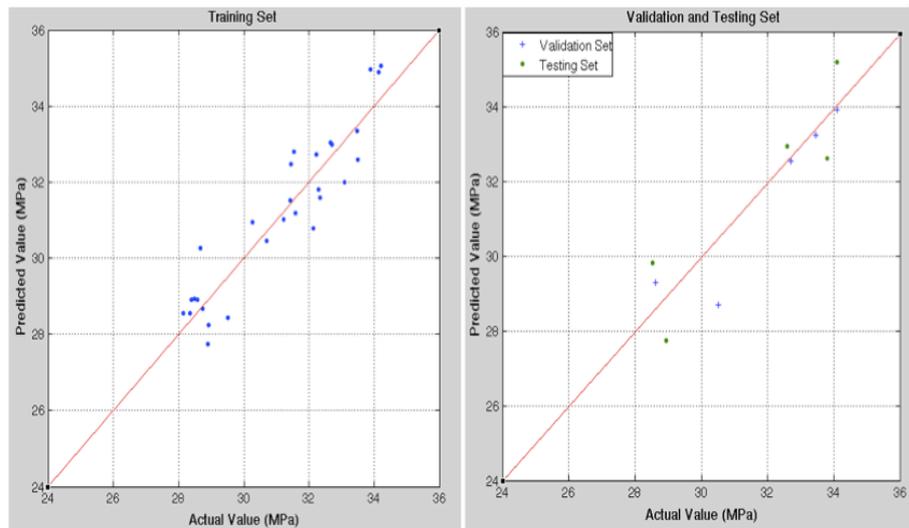


**Figure 6-9 - A comparison between the predicted values and the tested ones of K12**

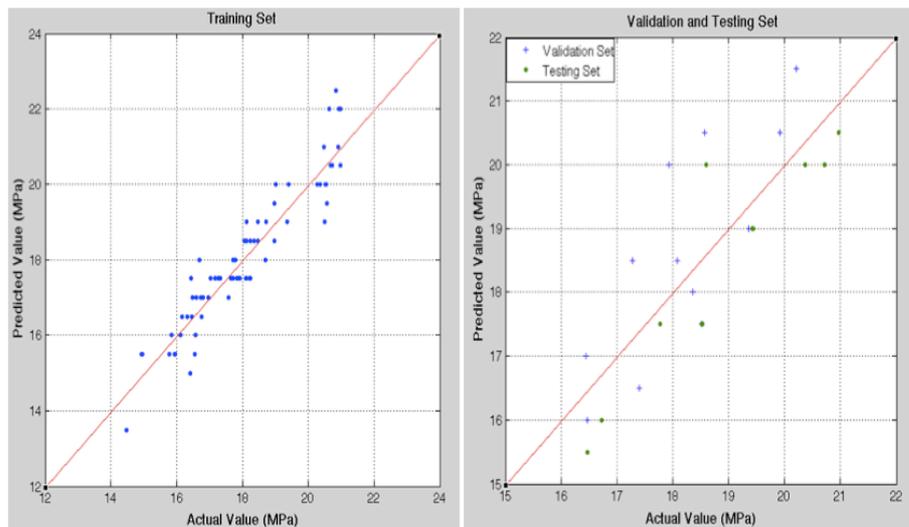


**Figure 6-10 - A comparison between the predicted values and the tested ones of K05**

By comparing Figures 6-8-6-12 with Figures 6-2-6-6, it can be noticed clearly that the  $E_c$  values are fitted more accurately when more variables related to the mixes and aggregate characteristics are used as the inputs of the ANN models.



**Figure 6-11 - A comparison between the predicted values and the tested ones of G11**



**Figure 6-12 - A comparison between the predicted values and the tested ones of D07**

As shown in Table 6-3, the correlation coefficient  $R^2$  values are all higher than

0.9975 and 0.996 in the training and validation and testing sets, respectively.

Noticeably, the MAPE values of the testing and validation sets are all very small, between 2% and 5.98%, and can be comparable with those in the training sets.

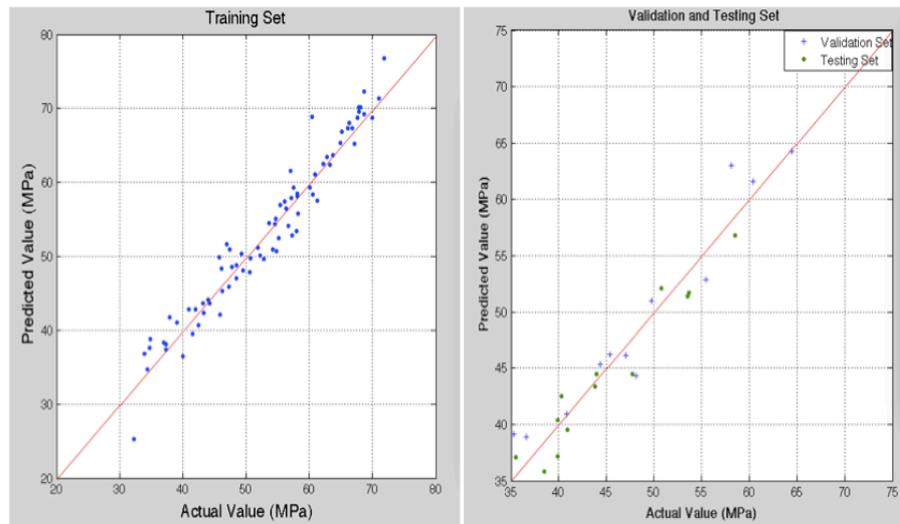
The results show that ANN is able to model the  $E_c$  of RAC accurately when suitable input variables are selected, irrespective of the types and sources of RA used.

#### **6.4 MODELING THE COMPRESSIVE STRENGTH OF RAC BY USING THE MIXS AND AGGREGATE CHARACTERISTICS**

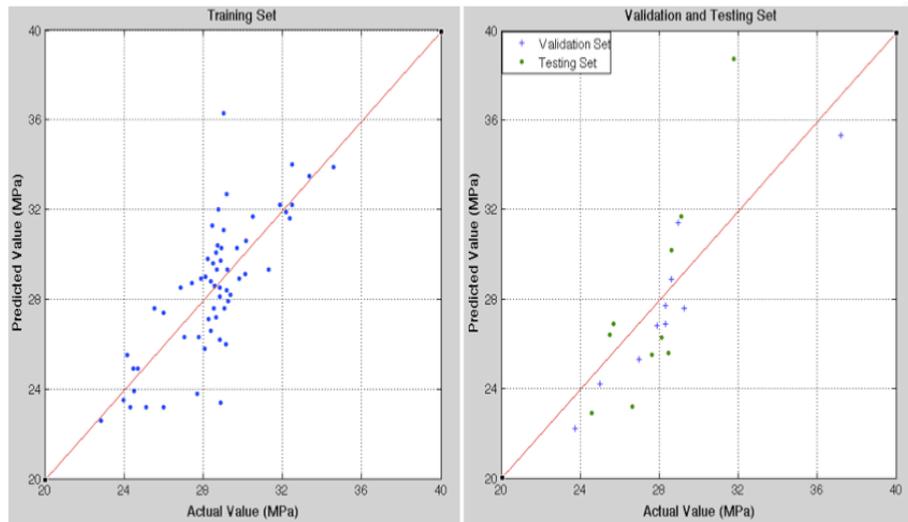
Similarly, the same input variables are used for the ANN models for the  $f_{cu}$  of RAC as shown in Table 6-2. The performance of all ANN models, reflected by  $R^2$ , RMS and MAPE, are shown in Table 6-4. Figures 6-13- 6-17 also indicate the performance of each model in the training, the validation and the testing sets, respectively.

**Table 6-4 - Networks parameters and the performance**

Sets	Index	K06	K12	K05	G11	D07
Total No.		104	47	30	39	94
<b>Training</b>	Number	78	35	22	29	70
	R <sup>2</sup>	0.9978	0.9978	0.9984	0.9981	0.9991
	MAPE (%)	3.92	4.27	4.61	3.57	2.91
	RMS	2.5377	1.9295	1.0732	2.5144	1.0738
<b>Testing</b>	Number	13	6	4	5	12
	R <sup>2</sup>	0.9982	0.9893	0.9974	0.9933	0.9976
	MAPE (%)	4.01	7.06	6.75	6.39	5.02
	RMS	1.9276	3.0088	1.2921	5.2856	1.7396
<b>Validation</b>	Number	13	6	4	5	12
	R <sup>2</sup>	0.9976	0.9976	0.999	0.9981	0.9978
	MAPE (%)	4.05	6.02	3.36	3.96	5.3
	RMS	2.5463	1.4757	1.0057	2.0396	1.8963

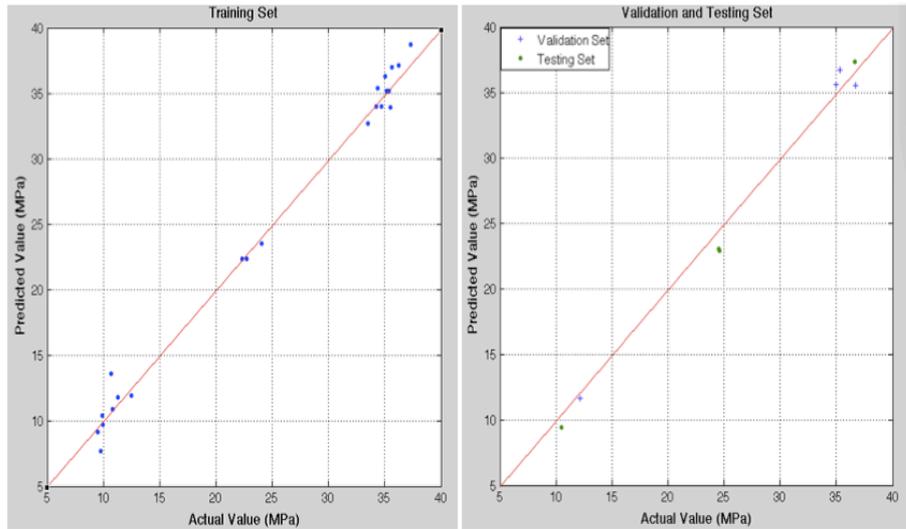


**Figure 6-13 - A comparison between the predicted values and the tested ones of K06**

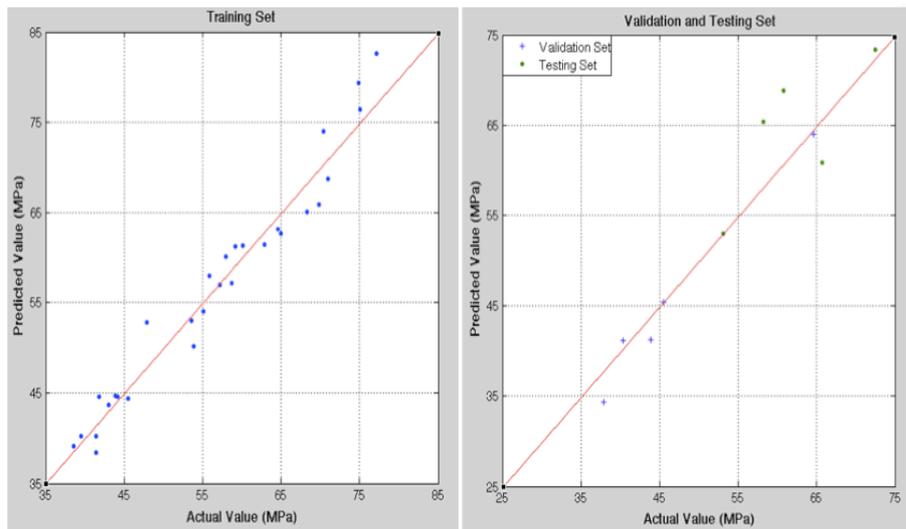


**Figure 6-14 - A comparison between the predicted values and the tested ones of K12**

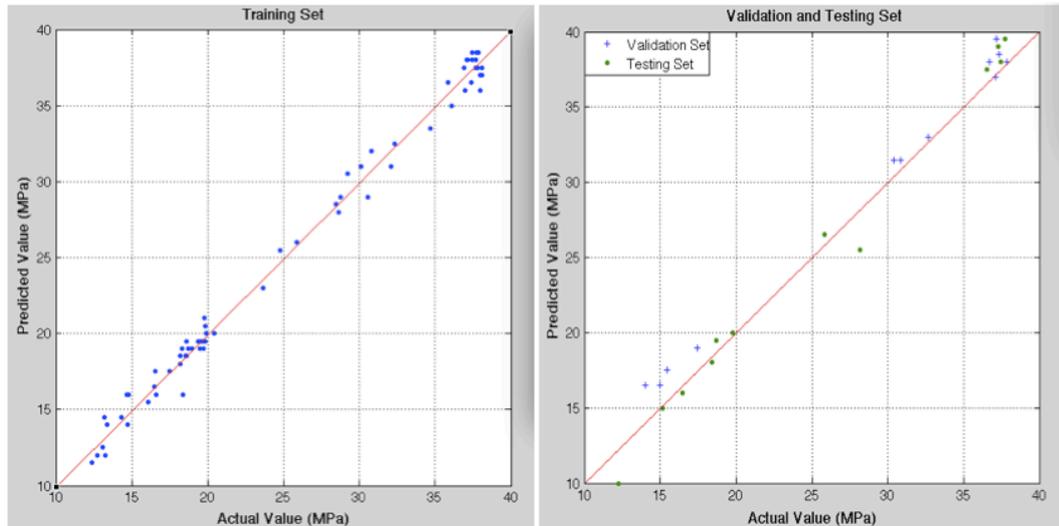
Similar to the performance of ANN models for  $E_c$ , the use of ANN models with suitable input variables is also able to produce accurate prediction of the  $f_{cu}$  values. The correlation coefficients  $R^2$  all exceed 0.9933 in all datasets, and the MAPE values are range from 2.91% to 4.61%. Although the MAPE values of some datasets in the testing and validation sets are slightly higher, at about 6-7%, the errors are still be acceptable.



**Figure 6-15 - A comparison between the predicted values and the tested ones of K05**



**Figure 6-16 - A comparison between the predicted values and the tested ones of G11**



**Figure 6-17 - A comparison between the predicted values and the tested ones of D07**

## 6.5 LIMITATIONS

Although the constructed ANN model for the dataset used in predicting the  $f_{cu}$  or  $E_c$  of RAC performed well, it does not mean that the models have generalization abilities for other datasets due to the following reasons:

- Only one source of RA was used in each of the dataset of Kou, Kotrayothar and Koulouries, so it may be unreliable when using the developed models to evaluate the properties of RAC made RAs from some other sources. As pointed out in the Chapter 2, the characteristics of NA and RAs (compositions, aggregate type, moisture state, gradation, maximum particle size of coarse aggregate, crushing method of RA, etc.) play important roles in affecting the properties of RAC. As

such, the accuracy of ANN model may be improved if some of these characteristics can be selected as the input variables.

- For ANN model, one limitation is that the values of each input variable used for testing should be in the same ranges of that used for training. Accordingly, the predictions produced will be also in the ranges of the outputs of the training set. It can be noticed from Table 6-2 that the ranges of input variables in each dataset are not wide enough for generalization.
- The special features of some datasets must be noticed. For K06, in addition to the traditional concrete mixes, fly ash was adopted as the replacement or addition of cement, and steam curing of the prepared concrete was used. Similarly, air-entraining agent, used in K05, was not adopted by the other datasets. In such cases, the applications of the constructed models may be limited.
- The type of cement used in each dataset is not always the same. The cement type used in K06 was OPC 52.5, while that used in the other literatures was OPC 42.5N. The predictions of the ANN model may be poor if the difference in cement type is ignored.

## **6.6 SUMMARY**

Through collecting data from 5 published literatures, five ANN models are

established in this chapter to predict the  $f_{cu}$  and  $E_c$  of RAC for each selected dataset. The following conclusions can be drawn:

- When using  $f_{cu}$  of RAC as the only input variable to model the corresponding elastic modulus through ANN, the approximation capability of ANN is proved, with  $R^2$  in the training set of each dataset over 0.993. However, the performance in the testing and validation sets is not as good, and some MAPE values in the testing set even exceed 10%. This is mainly due to that the factors affect the  $f_{cu}$  and  $E_c$  of RAC may be not the same, and the relative importance of such factors play on the two properties are also different.
- When more parameters related to the mix proportions and aggregate characteristics are included as the input variables, the constructed models can produce better predictions for both the  $E_c$  and  $f_{cu}$ . For models on  $E_c$ , the  $R^2$  values are all higher than 0.9975 and 0.996 in the training set and validation and testing sets, respectively, and the MAPE values of all models in the testing and validation sets are very small, between 2% and 5.98%. For models on  $f_{cu}$ , the  $R^2$  values exceed 0.9933 in all data sets, and the MAPE values range from 2.91% to 4.61% in the training set. Although the MAPE

values of some datasets in the testing and validation sets are slightly higher, about 6% -7%, the values are still acceptable.

- When using ANN to train and test data from the same source, the constructed model is capable of modeling the  $E_c$  or  $f_{cu}$  of RAC when suitable input variables are selected, no matter how many types of RAs are used, whether mineral or chemical admixtures are adopted in the mixtures, and which curing method is adopted.
- However, it is difficult for a specific ANN model developed from a specified dataset to produce good predictions for other datasets due to the limitations of ANN and the dataset itself.

# **CHAPTER 7: USING ANN FOR PREDICTING THE MECHANICAL PROPERTIES OF RAC MADE WITH RAs DERIVED FROM DIFFERENT SOURCES**

## **7.1 INTRODUCTION**

The better ability of ANN in fitting the mechanical properties of RAC relative to that of the regression analysis has been demonstrated in the last chapter. When the data used for training and testing of the ANN models are from a same source, the networks are able to model the  $E_c$  or  $f_{cu}$  of RAC quite accurately.

But as stated in Chapter6, the main limitation of the developed ANN model is only a few factors have been taken into account, and the range of the values of the factor is also narrow. A systematic combination of dataset from different literatures through ANN may be able to solve this problem, since the use of networks can learn the influence of inputs to the output from each respective dataset.

This chapter tries to establish improved ANN models with generalization

abilities, similar to an expert system, in predicting the  $f_{cu}$  and  $E_c$  of RAC. For each model, a large amount of data is collected from different published literatures, in which the factors that will be selected as the input variables are indicated. The improved ANN models are then applied to predict the corresponding properties of RAC prepared in Chapter 4. The predicted results are also compared with the experimental test results. Sensitivity analysis is finally conducted to examine the influence of each input variable on the  $f_{cu}/E_c$  of RAC after the construction of the models.

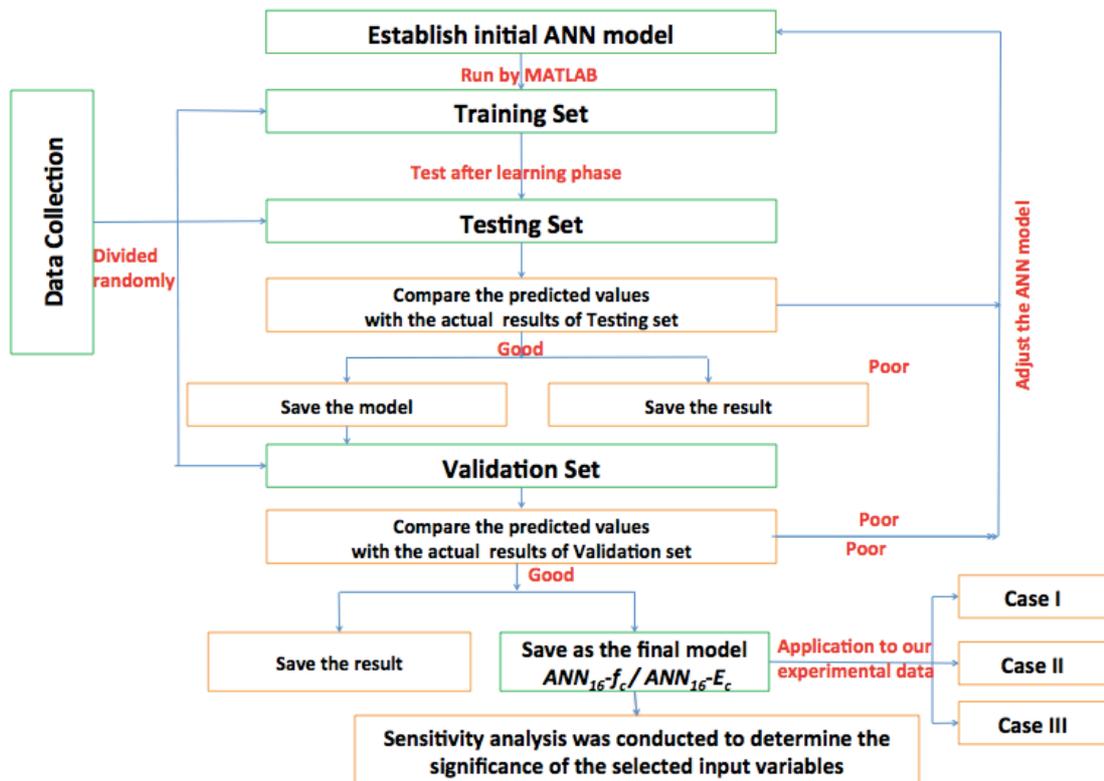


Figure 7-1 - Flow chart of development of ANN models

## 7.2 THE ANN MODEL FOR ELASTIC MODULUS OF RAC

The flow chart describing the development of the ANN models in this chapter is shown in Figure 7-1, Based on the development work described in Chapters 4-6, the types and number of input variables for the models have been determined and are given in Table 7-1.

**Table 7-1 - Ranges of variables of data sets in the constructed ANN models**

Factors	Input and output Variables (Unit)	Data used in $ANN_{16-E_c}$	
		Min.	Max
			.
	$C$ ( $kg/m^3$ )	180	750
	$W/C$	0.3	1.03
<b>Mix proportions</b> (5 variables)	$A/C$	1.75	10.9
	$S_p$	0.18	0.57
	$r(\%)$	0	100
	$W_a(\%)$	0.26	28
<b>Characteristic of coarse aggregate</b> (3 variables)	$SG_{SSD}$ ( $g/cm^3$ )	1.44	2.79
	$D_{CA}$ ( $mm$ )	16	32
	$\delta(\%)$	0	6
<b>Constituents of recycled coarse aggregate</b> (2 variables)	$m(\%)$	0	100
	$k$	1	4
<b>Type and preparation methods of coarse aggregate</b> (3 variables)	$T_{NA}$	0	3
	$T_{RA}$	0	3
	$S_C$	0.2	0.25
<b>Cement type</b> (2 variables)	$G_C$	32.5	52.5
	$C_S$	1	1.05
<b>Specimen size</b> (1 variable)			
<b>Output value</b> (1 variable for each model)			
<b>28 day elastic modulus</b>	$E_c$ ( $GPa$ )	13.5	43.7

It should be noted that there are still some other factors that may affect the  $E_c$  or  $f_{cu}$  of RAC, such as mixing methods, and the fineness modulus of sand, etc. However, as few literatures have reported data with all these factors, the inclusion of such factors into the input variables will significantly reduce the amount of data that can be adopted in the ANN models. Therefore, they are ignored in this study.

### **7.2.1 The selection of input and output variables**

For predicting the  $E_c$  of RAC using ANN models, an appropriate selection of input variables is essential. As some of the factors that may affect the  $E_c$  of concrete are qualitative indexes that are not suitable to be used directly in ANN, a transformation of such qualitative indexes into quantitative ones is necessary. As can be seen in Table 7-1, the input and output variables, together with the detailed description of how to convert the qualitative factors into the required ones are described.

#### ***Mix proportions (5 variables)***

The amounts of different constituents, such as W, C, fine and coarse aggregates contents are undoubtedly the main factors affecting the  $E_c$  of the concrete. In this

Chapter, C, W/C, A/C, S<sub>p</sub> and r are selected as the factors for mix proportions.

***Aggregate characteristics (8 variables)***

(1) Characteristic of coarse aggregate (3 variables)

The characteristics of coarse aggregates are very important, such as maximum particle size (D<sub>CA</sub>), SG<sub>SSD</sub> and W<sub>a</sub> values, which affect the RAC strength. As the sources and crushing processes from which the RAs are obtained could be quite different, the properties of the coarse aggregates used vary greatly.

In this study, the SG<sub>SSD</sub> and W<sub>a</sub> values of the mixed coarse aggregate are calculated by Eq. (7-1) - Eq. (7-3).

$$r = (M_{RA}/SG_{RA}) / (M_{RA}/SG_{RA} + M_{NA}/SG_{NA}) \quad (7-1)$$

$$SG_{CA} = [SG_{RA} \times r + SG_{NA} \times (100-r)] / 100 \quad (7-2)$$

$$W_a = [W_{aRA} \times r + W_{aNA} \times (100-r)] / 100 \quad (7-3)$$

where  $r$  (replacement ratio, %) is the volume fraction of coarse RA in RAC;  $M_{RA}$  and  $M_{NA}$  are the quantities ( $kg/m^3$ ) of coarse RA and NA in RAC, respectively;  $SG_{CA}$ ,  $SG_{NA}$  and  $SG_{RA}$  ( $g/cm^3$ ) are saturated surface dry specific gravity of the mixed coarse aggregates, natural coarse aggregates and recycled coarse

aggregates, respectively;  $W_a$ ,  $W_{aNA}$  and  $W_{aRA}$  are the water absorption values (%) of the mixed coarse aggregates, natural coarse aggregates and recycled coarse aggregates, respectively.

(2) Constituents of recycled coarse aggregate (2 variables)

Also, RA produced from old concrete test specimens are generally 100% crushed concrete, while RA obtained from old buildings or old pavement usually contain small amounts of soft soils, natural stones, clay bricks, and other impurities like paper, wood, glass, tiles and metals (Poon et al. 2004). A number of studies (Agrela et al. 2011; Yang et al. 2011) have been done on assessing the effect of mixed recycled aggregates on the properties of RAC and the results suggested a higher level of masonry content in RA can be allowed for concrete applications but the possible adverse effect of the impurities on the properties of RAC, especially the durability, should not be ignored (Chen et al. 2003; Poon and Chan 2007; Debieb et al. 2010). Therefore, the calculation of masonry and impurity content of coarse aggregate used in ANN are as Equations 7-4 and 7-5, respectively.

$$m = r \times m_{RA} / 100 \quad (7-4)$$

$$\delta = r \times \delta_{RA}/100 \quad (7-5)$$

where  $m$  and  $m_{RA}$  are masonry content of coarse aggregate and  $RA$  in  $RAC$ , respectively;  $\delta$  and  $\delta_{RA}$  are impurity content of coarse aggregate and  $RA$  in  $RAC$ , respectively.

### (3) Type and preparation methods of coarse aggregate (3 variables)

The data used in the training set of the ANN models are collected from published literature based on the results of other studies. The types and processing methods of the RAs used in these past studies will affect their properties (e.g. moisture states, level of contamination, % of adhered mortar etc.). Zega et al. (2009) indicated that the type of NA used in the old concrete played an important role in affecting the properties of RA, and the importance of which, sometimes is even higher than the effect of the W/C of the virgin concrete. Besides, the influence of the parent concrete of RA (Padmini et al. 2009) and crushing process (Etxeberria et al. 2007a) on RA also should not be overlooked. The moisture states (oven dry, air dry or SSD) of the RA also should be taken into account (Gunaydin and Dogan 2004). In this study, NA type, RA type and moisture states of coarse aggregate are selected as the input variables. Indexing this non-quantitative parameters are illustrated as follows:

For NA type,  $T_{NA}$  is a coefficient depends on the quality (Mehta and Monteiro2006) and quantity of NA used in RAC:

- 0 = no NA is used;
- 1 = sandstone or gravel is used as NA;
- 2 = limestone or dolomite stone is used as NA;
- 3 = granite is used as NA.

For RA type,  $T_{RA}$  is a coefficient depends on the crushing process and quantity of RA used in RAC:

- 0 = no RA is used;
- 1 = demolition waste collected from recycling plants, where several crushing processes are generally adopted, is used as RA;
- 2 = demolition waste crushed by hammer or simple crusher in laboratory is used as RA;
- 3 = old concrete specimen crushed by hammer or simple crusher in laboratory is used as RA.

For moisture condition,  $k$  is a coefficient represents the moisture state of the

coarse aggregate:

- 1 = coarse aggregate is used in oven dry condition when mixed;
- 2 = coarse aggregate is used in air dry condition without pre-wetted when mixed;
- 3 = coarse aggregate is used in air dry condition with pre-wetted for a few minutes when mixed;
- 4 = coarse aggregate is pre-wetted for 24h to SSD or wet condition when mixed;

For example, for RAC made with 50% crushed granite replaced by RA in dry condition, and the RA is crushed from old concrete cube by hammer, the input data of  $T_{NA}$ ,  $T_{RA}$  and  $k$  in ANN model are 3, 3 and 1, respectively.

### ***Cement type (2 variables)***

The type of cement used also plays an important part in affecting the mechanical properties of RAC (Mas et al. 2012). In this study, the cement type used in the concrete mixes of the data sets of the ANN model is transformed into two quantitative variables as follows:

(1)  $G_C$  is a coefficient depends on the strength grade of cement used in RAC:

- 32.5 = CEM 32.5;

➤ 42.5 = CEM 42.5;

➤ 52.5 = CEM 52.5.

(2)  $S_C$  is a coefficient according to the rate of hydration of the cement used in

RAC (Jankovic et al. 2011):

➤ 0.2 = rapid hardening high strength cements (R), such as CEM 42.5R and CEM 52.5;

➤ 0.25 = normal and rapid hardening cements (N), such as CEM 32.5R and CEM 42.5;

For example, for RAC made with CEM 42.5R as cement, the input data of  $G_C$  and  $S_C$  in ANN model are 42.5 and 0.2, respectively.

### **Specimen size (1 variable)**

Taking into account that different researchers used specimens of different sizes (viz. 100×200mm and 150×300mm cylinders), the influence of the size of the specimens should be considered (Baalbaki et al. 1992). The corresponding quantitative variables ( $C_S$ ) used in the ANN are as follows:

➤ 1 = 100 × 200 mm cylinders are used to test the  $E_c$  values;

- 1.05 = 150 × 300 mm cylinders are used to test the  $E_c$  values.

### **Output parameter**

Elastic modulus: The 28-day  $E_c$  values used in the training set are taken from the published sources as mentioned earlier.

### **7.2.2 Data collection**

Although thousands of data related to the  $E_c$  of RAC are collected from published literatures, only part of them can be adopted as the dataset to construct ANN model, since the information of some factors, selected as the inputs of networks, may be not available in these literatures.

According to the input variables determined in Section 7.2.1, a total 324 sets of experimental data from 21 international published literatures (de Juan and Gutierrez2004; Koulouris2005; Kou 2006; Dhir and Paine 2007; Hu 2007; Casuccio et al. 2008; Kou and Poon 2008 & 2011; Yanget al.2008; Ahmed 2009; Bassan et al. 2009; Cabo et al. 2009; Gomez-Soberon 2009; Zega and Di Maio 2009; Belen et al. 2011a & 2011b; Guan 2011; Obispo 2011; Rao et al. 2011; Safiuddin et al. 2011; Vieira et al. 2011) are adopted as the sample data, among

which 224, 50 and 50 datasets are used for training, testing and validation, respectively. Besides, the author's own experimental results (see Chapter 4: Cases I- III) are used as cases to test the generalization capacity of the constructed model. The performance of networks model in Cases I- III is also compared with that of the traditional regression analysis, respectively.

### **7.2.3 Construction of the ANN model**

The BPNN, adopted in this research, has 16 neurons (variables) in the input layer and one unit in the output layer as illustrated in Figure 7-2. The values of network parameters considered in this approach are as follows: number of hidden layers = 0, 1, and 2; number of hidden neurons = 5-50; learning rate = 0.01, 0.1, 0.3, 0.5, 0.7, 0.9, 1.0, and 2.0; momentum factor = 0.0, 0.3, 0.5, 0.7, 0.9 and 1; and learning cycles = 500, 1000, 5000, 10000, 15000 and 20000 (each cycle covers the entire database available for training).

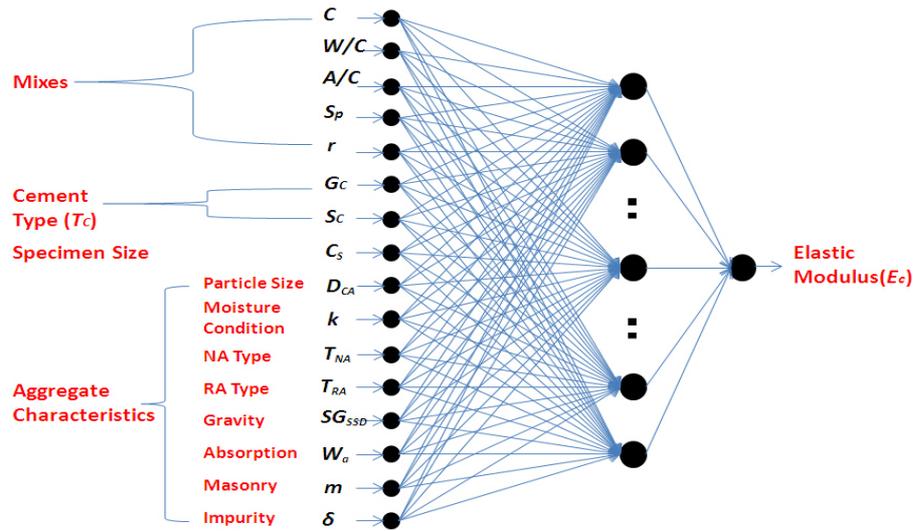


Figure 7-2-The constructed ANN model ( $ANN_{16-E_c}$ ) for elastic modulus

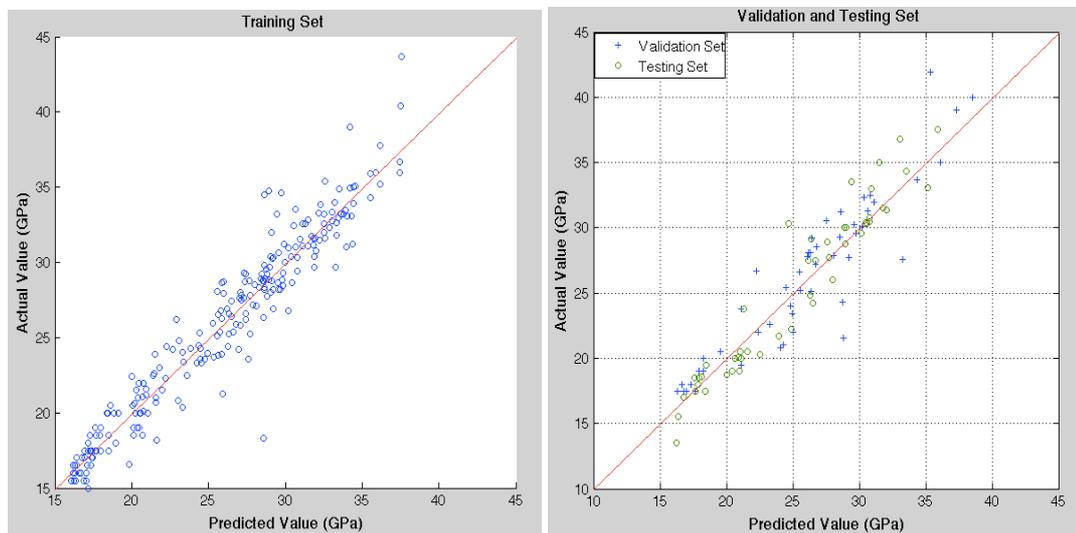
Based on the error of integral testing and validation sets after a series of trials, the best network architecture and parameters that maximize the  $R^2$  values of the testing data are as follows:

- 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

#### 7.2.4 Results and discussion

The performance of  $ANN_{16-E_c}$ , reflected by indexes like  $R^2$ , RMS and MAPE, is

shown in Table 7-2. The indexes in the Table, as well as the plot of predicted vs actual values shown Figure 7-3 all demonstrate that ANN<sub>16</sub>-E<sub>c</sub> is capable of predicting the E<sub>c</sub> values adequately. In addition, Table 7-2 also shows the application of the constructed ANN<sub>16</sub>-E<sub>c</sub> to Case I-Case III can also produce good predictions with MAPE values between 4.65% and 7.13%, while the correlation coefficient R<sup>2</sup> are in the range of 0.9904- 0.995.



**Figure 7-3 - The performance of ANN<sub>16</sub>-E<sub>c</sub>**

**Table 7-2- Performance of ANN<sub>16</sub>-E<sub>c</sub> in all sets and Cases**

Sets	$R^2$	$RMS$	$MAPE$ (%)
<b>Training</b>	0.9966	1.537	4.152
<b>Testing</b>	0.992	2.311	5.88
<b>Validation</b>	0.9918	2.346	6.574
<b>Case I</b>	0.995	1.9603	4.65
<b>Case II</b>	0.9923	2.3585	5.86
<b>Case III</b>	0.9904	2.2365	7.13

**Table 7-3- Predicted results of ANN<sub>16</sub>-E<sub>c</sub> in Case I**

	Experimental results			Predicted results	
	<i>E<sub>c</sub> (GPa)</i>	<i>SD (GPa)</i>	<i>COV (%)</i>	<i>E'<sub>c</sub>(GPa)</i>	<i>Error (%)</i>
<b>Case I</b>	32.3	1.98	6.13	36.78	13.88
	26.18	1.4	5.12	25.26	3.52
	27.26	0.3	1.11	26.36	3.3
	27.05	0.97	3.59	26.22	3.06
	26.85	1.38	5.14	26.29	2.08
	26.8	0.03	0.1	26.25	2.06
<b>Average</b>			3.53		4.65

A detailed comparison between the predictive values and the experimental ones for Case I-Case III are as shown in Table7-3- Table 7-5. It can be noticed that most of the predictions have an error lower than 10%. Relative to the coefficient of variations (COV) of the experimental test results, the MAPE values of the predictions by ANN are just slightly higher, about 1.12, 0.82 and 2.77%, respectively. The MAPE value of 7.13% for Case III is slightly higher, and it may be mainly due to the lack of sufficient data related to the RA containing added masonries in the training set of the networks.

**Table 7-4- Predicted results of ANN<sub>16</sub>-E<sub>c</sub>in Case II**

	Experimental results			Predicted results	
	<i>E<sub>c</sub></i> (GPa)	<i>SD</i> (GPa)	<i>COV</i> (%)	<i>E'<sub>c</sub></i> (GPa)	<i>Error</i> (%)
<b>Case II</b>	25.1	0.62	3.07	24.44	2.64
	20.85	0.4	2.42	21.66	3.86
	21.9	0.52	2.39	20.29	7.35
	20.49	2.89	15.68	20.88	1.91
	30.68	0.41	1.63	29.86	2.68
	28.86	0.6	2.07	24.69	14.46
	24.46	0.78	3.18	22.88	6.44
	26.55	0.09	0.35	23.81	10.32
	32.36	0.38	1.16	33.39	3.18
	29.42	5.01	19.53	27.49	6.55
	24.61	1.24	5.03	25.85	5.02
	28.5	4.22	16.54	27.19	4.58
	35.43	1.36	3.96	35.8	1.05
	34.76	0.17	0.49	30.13	13.31
	29.52	0.27	0.91	28.20	4.49
	30.62	0.69	2.21	29.93	2.26
<b>Average</b>			5.04		5.63

#### ***Application of ANN<sub>16</sub>-E<sub>c</sub> to Case I***

As shown in Figure 7-4, both the predicted and experimental results indicate that the E<sub>c</sub> values of all RAC are much lower than that of the NAC. The chart comparison between the predicted results and the tested ones of Case I is shown in Figure 7-4. Among all the five recycled concrete mixtures, the largest and lowest predictions by ANN<sub>16</sub>-f<sub>c</sub> are RC1 and RC2, respectively, which also match the experimental results.

*Application of ANN<sub>16</sub>-E<sub>c</sub> to Case II*

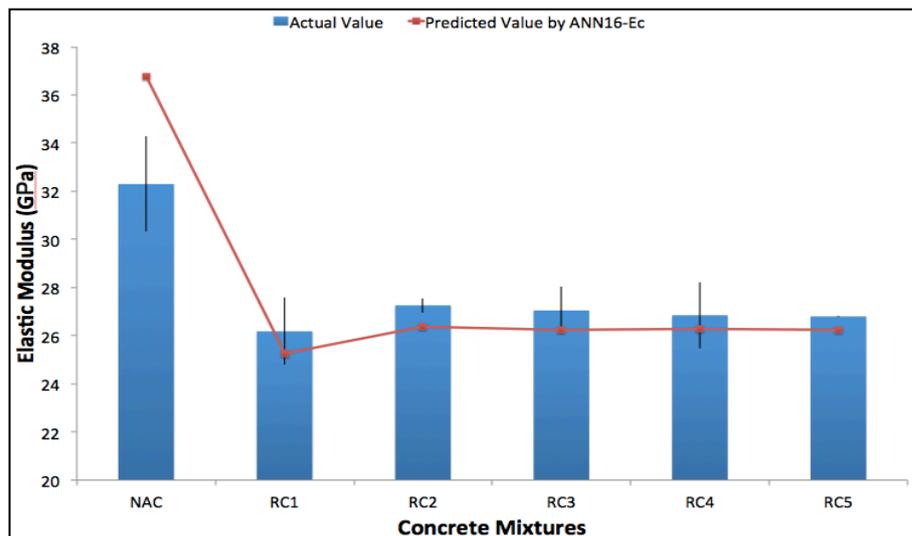
**Table 7-5- Predicted results of ANN<sub>16</sub>-E<sub>c</sub> in Case III**

	Experimental results			Predicted results	
	<i>E<sub>c</sub></i> (GPa)	<i>SD</i> (GPa)	<i>COV</i> (%)	<i>E'<sub>c</sub></i> (GPa)	<i>Error</i> (%)
<b>Case III</b>	31.51	3.87	14.29	31.09	1.32
	30.94	0.25	0.87	28.62	7.5
	29.14	4.83	16.18	28.26	3.02
	27.09	0.29	1.07	27.9	2.98
	29.54	2.9	9.81	28.48	3.57
	27.5	1.1	4	27.99	1.78
	23.18	0.95	4.09	27.49	18.59
	30.45	1.62	4.82	31.17	2.36
	29.58	0.76	2.5	27.72	6.28
	26.78	0.81	3.04	24.59	8.16
	29.03	0.47	1.61	25.68	11.55
	27.1	0.34	1.21	23.4	13.66
	27	0.57	2.12	25.54	5.4
	26.69	0.2	0.74	22.55	15.5
	24.42	2.38	9.73	25.36	3.84
	24.15	0.45	1.85	21.38	11.46
	27.39	0.09	0.3	25.84	5.67
	25.69	0.34	1.3	23.6	8.15
	26.72	0.57	2.08	25.71	3.77
	24.55	1.35	5.49	22.60	7.96
<b>Average</b>			4.36		7.13

The detailed comparison of the predicted and the tested results in Case II is shown in Figure 7-5. According to the predictions, under the condition of the same W/C, the NAC has the highest E<sub>c</sub>, followed by recycled concrete made with RA6 and RA8, while the E<sub>c</sub> values of concrete made with RA7 are the

lowest. The trends are quite similar to the experimental results except for the C30 concrete. The test results show that the  $E_c$  of RAC made with RA7 is the largest when using the three types of RAs to fully replace NA to produce C30 concrete, although RA7 is regarded as the weakest among all the three RAs examined. This may be due to the strength of aggregate has little influence on the properties of concrete of lower strength.

Besides, the predicted elastic modulus of all concrete mixtures, prepared by either NA or RAs, increase gradually with the reduction of W/C. The prediction is also consistent with the experimental test results.



**Figure 7-4 - A comparison of the predictions by ANN<sub>16</sub>-E<sub>c</sub> with the test results in Case I**

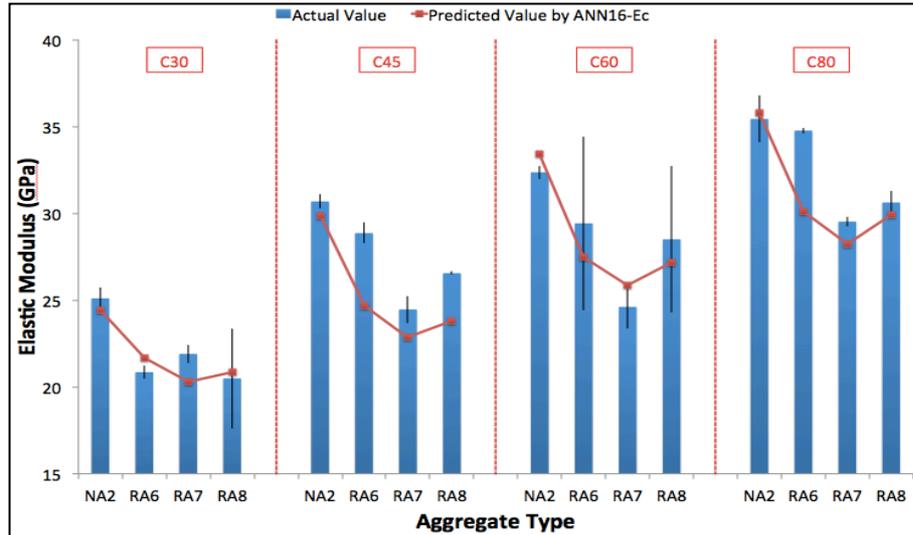


Figure 7-5 - A comparison of the predictions by ANN<sub>16</sub>-E<sub>c</sub> with the test results in Case II

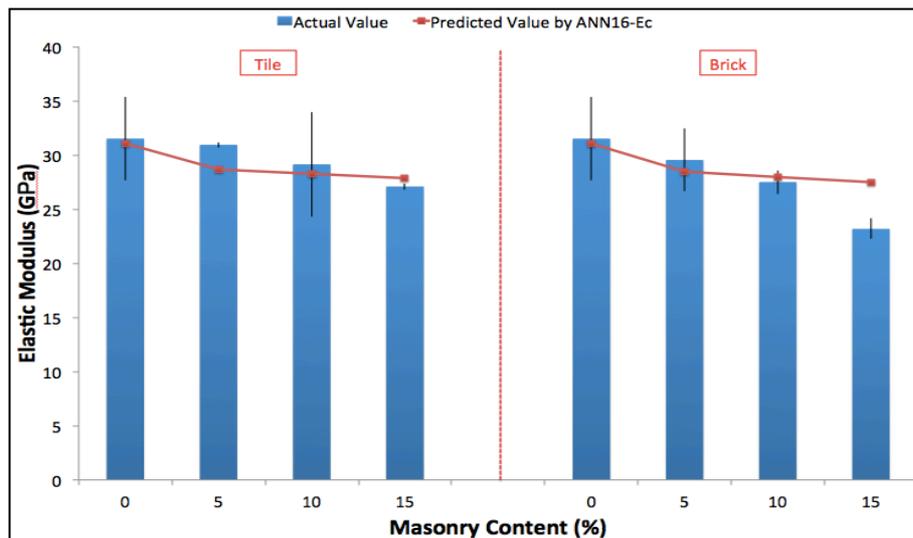


Figure 7-6 - E<sub>c</sub>-value predictions of ANN<sub>16</sub>-E<sub>c</sub> for NAC made with added masonry

### Application of ANN<sub>16</sub>-E<sub>c</sub> to Case III

For the concrete mixtures containing small amounts of crushed clay bricks or tiles, the comparisons of the predicted E<sub>c</sub> values and the experimental results are shown in Figure 7-6 to Figure 7-8.

According to the predictions, a general trend of reduction in  $E_c$  Values with the increase of the masonry percentage can be noticed from all the three Figures. The trend is also verified by the experimental results.

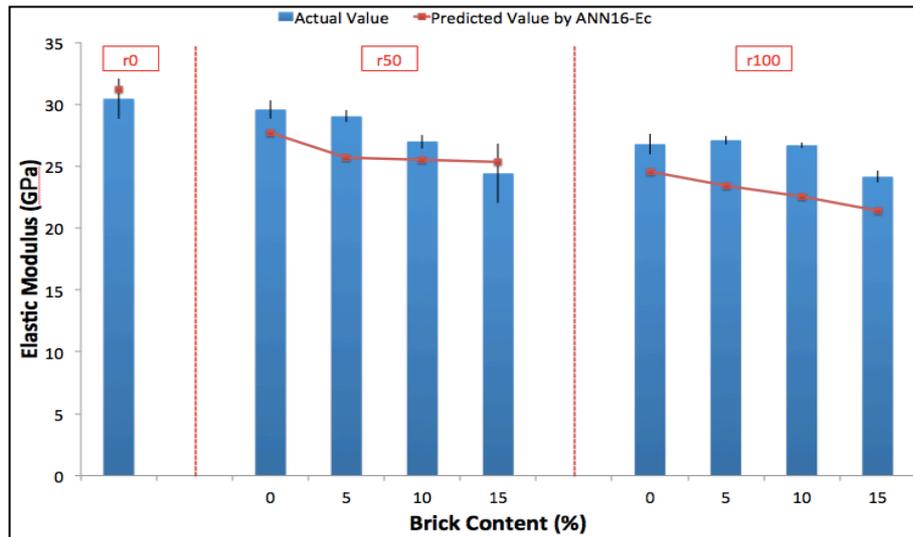


Figure 7-7 -  $E_c$ -value predictions of ANN<sub>16</sub>- $E_c$  for RAC made with crushed clay bricks

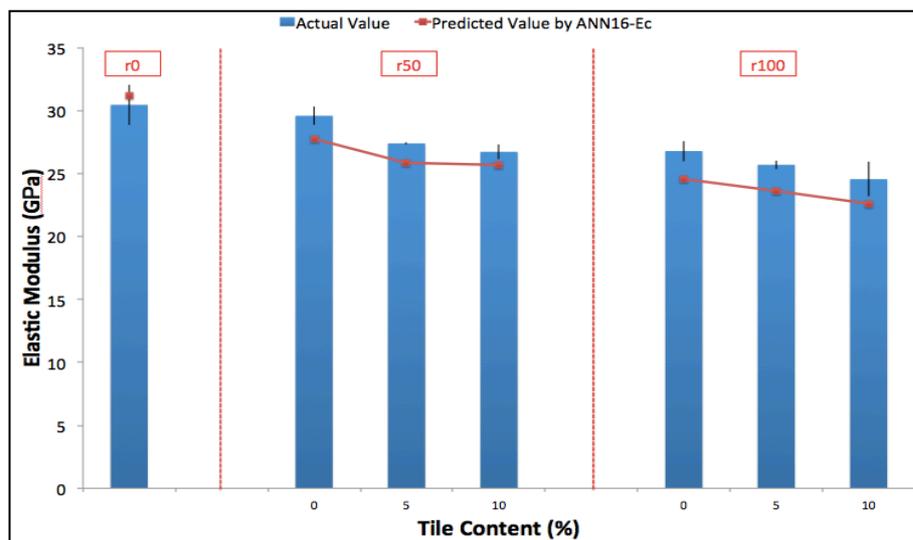


Figure 7-8 -  $E_c$ -value predictions of ANN<sub>16</sub>- $E_c$  for RAC made with crushed tiles

Above all, the constructed ANN model for  $E_c$  (ANN<sub>16</sub>- $E_c$ ) is not only able to produce good predictions in the testing and validation sets, but also be capable of applying to the Cases of our own experimental data. Relative to the predicted results based on the traditional regression analysis, which were discussed in the Chapter 5, steady and accuracy are proved to be the significant characteristics of ANN model.

## **7.3 THE ANN MODEL FOR COMPRESSIVE STRENGTH OF RAC**

### **7.3.1 The selection of input and output variables**

To ease analysis, the same input variables as those for  $E_c$  prediction are selected for constructing the networks model of  $f_{cu}$ . However, it should be noticed that  $C_s$  used in the networks for  $f_{cu}$  are as follows:

- 1 = 100mm cubes are used to test the  $f_{cu}$  values;
- 0.95 = 150mmcubes are used to test the  $f_{cu}$  values.

The ranges of the input and output variables of the model are shown in Table 7-6.

**Table 7-6 - Ranges of variables of data sets in the constructed ANN models**

Factors	Input and output Variables (Unit)	Data used in $ANN_{16-E_c}$	
		Min.	Max
			.
	$C$ ( $kg/m^3$ )	250	750
	$W/C$	0.248	0.74
<b>Mix proportions</b> (5 variables)	$A/C$	1.752	7.86
	$S_p$	0.286	0.57
	$r(\%)$	0	6
	$r(\%)$	0	100
	$W_a$ (%)	0.3	28
<b>Characteristic of coarse aggregate</b> (3 variables)	$SG_{SSD}$ ( $g/cm^3$ )	1.926	2.72
			5
	$D_{CA}$ ( $mm$ )	10	32
<b>Constituents of recycled coarse aggregate</b> (2 variables)	$\delta$ (%)	0	10.4
	$m$ (%)	0	30
<b>Type and preparation methods of coarse aggregate</b> (3 variables)	$k$	1	4
	$T_N$	0	3
	$T_R$	0	3
<b>Cement type</b> (2 variables)	$S_C$	0.2	0.25
	$G_C$	32.5	52.5
<b>Specimen size</b> (1 variable)	$C_S$	0.95	1
<b>Output value</b> (1 variable)			
<b>28 day compressive strength</b>	$f_{cu}(MPa)$	23	100

### 7.3.2 Data collection

According to the input variables determined in Section 7.3.1, a total of 409 sets of experimental data from 23 international published literatures (Ravindrarajah and Tam 1985; Barra and Vazquez 1998; de Pauw and Thomas 1998; Knights

1998; Dhir et al. 1999; Goncalves 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; Corinaldesi 2010 & 2011; Meddah et al. 2010; Belen et al. 2011a & 2011b; Guan 2011; Vieira et al. 2011; Kotrayothar 2012) are adopted as the sample data, among which 309, 50 and 50 data are used for training, testing and validation, respectively. Besides, the author's own experimental results (See Chapter 4: Cases I- III) are used as cases to test the generalization capacity of the constructed model.

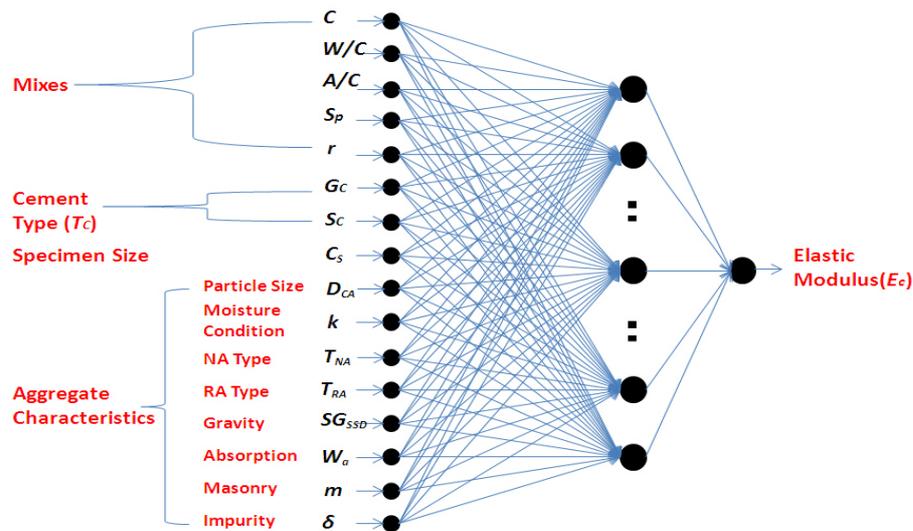


Figure 7-9 - The constructed ANN model ( $ANN_{16-f_{cu}}$ ) for compressive strength

### 7.3.3 Construction of the ANN model

As illustrated in Figure 7-9, the constructed ANN model for  $f_{cu}$  also has 16 neurons (variables) in the input layer and one unit in the output layer. The network architecture and parameters are also chosen 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

### 7.3.4 Results and discussion

**Table 7-7 - Performance of ANN<sub>16-f<sub>cu</sub></sub>**

Sets	$R^2$	<i>RMS</i>	<i>MAPE (%)</i>
<b>Training</b>	0.9955	3.14	5.518
<b>Testing</b>	0.9912	4.334	6.558
<b>Validation</b>	0.9925	4.048	6.562
<b>Case I</b>	0.9969	3.7214	5.51
<b>Case II</b>	0.9932	3.7214	5.66
<b>Case III</b>	0.9979	2.2484	3.51

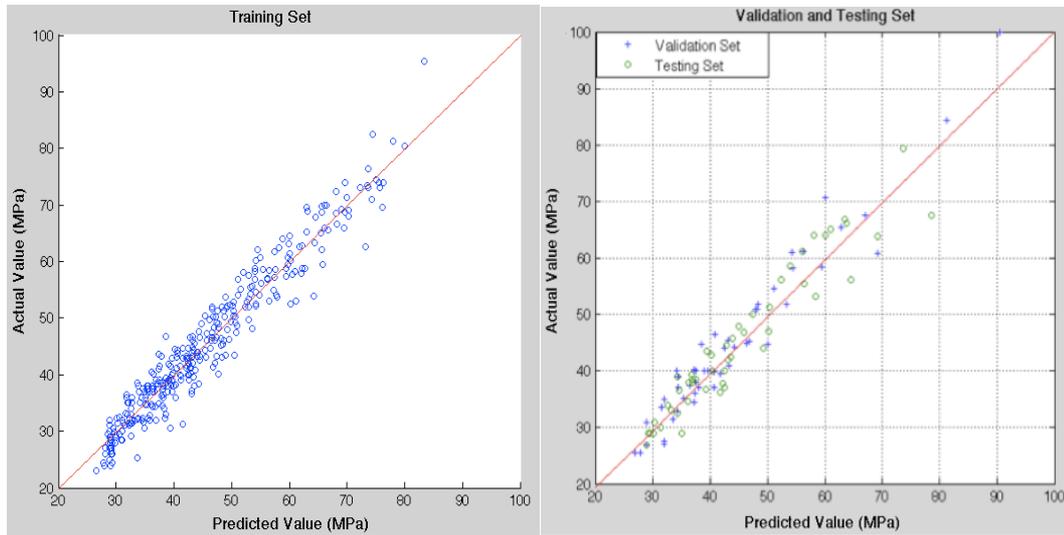
The performance of ANN<sub>16-f<sub>cu</sub></sub> can be seen in Table 7-7 and Figure 7-10. Similar to ANN<sub>16-E<sub>c</sub></sub>, ANN<sub>16-f<sub>cu</sub></sub> also has good fitting in the training, testing and validation sets, with  $R^2$  values of 0.9955, 0.9912 and 0.9925, respectively.

Additionally, the application of ANN<sub>16-f<sub>cu</sub></sub> to the researcher's own experimental data (Case I - Case III) all has satisfactory predictions, as shown in Table 7-7.

Compared with the performance of ANN<sub>16-f<sub>cu</sub></sub> in the training set, lower MAPE

and higher  $R^2$  values are produced when the model is applied to Case I - Case III.

This further proves the model's generalized capacity.



**Figure 7-10 - The performance of ANN<sub>16</sub>- $f_{cu}$**

### ***Application of ANN<sub>16</sub>- $f_c$ to Case I***

The comparison between the predicted results and the tested ones of Case I is shown in Table 7-8 and Figure 7-11. Similar trends are noticed from the predicted and actual  $f_{cu}$  values. Among the five RAC mixtures, RC1 and RC2 have the largest and lowest predicted  $f_{cu}$  values, respectively. This is also verified by the experimental results.

**Table7-8- Predicted results of ANN<sub>16</sub>-f<sub>cu</sub> in Case I**

	Experimental results			Predicted results	
	$f_{cu}$ (MPa)	SD (MPa)	COV (%)	$f'_{cu}$ (MPa)	Error (%)
Case I	69.6	2.62	3.76	74.26	6.69
	59.4	2.07	3.48	64.15	8.00
	69.8	0.68	0.97	66.13	5.26
	67.8	1.63	2.4	65.56	3.31
	68.7	1.27	1.85	65.55	4.58
	62.1	1.86	3	65.32	5.19
<b>Average</b>			2.58		5.51

**Table 7-9 - Predicted results of ANN<sub>16</sub>-f<sub>cu</sub> in Case II**

	Experimental results			Predicted results	
	$f_{cu}$ (MPa)	SD (MPa)	COV (%)	$f'_{cu}$ (MPa)	Error(%)
Case II	34.5	0.9	2.98	35.44	2.71
	35	0.18	0.65	35.81	2.30
	29.2	2.11	7.24	32.69	11.96
	27.7	3.31	12.92	31.07	12.15
	48.3	2.39	4.94	48.36	0.13
	47.6	0.55	1.17	45.64	4.13
	42	1.06	2.53	43.84	4.37
	42.9	1.2	2.81	42.28	1.45
	61.6	1.36	2.21	62.47	1.41
	60	2.46	4.11	52.17	13.05
	53.7	2.02	3.76	51.35	4.38
	53.2	1.97	3.71	49.87	6.26
	80.5	2.37	2.95	78.66	2.29
	78.2	4.18	5.37	64.48	17.54
	71.2	0.28	0.4	67.17	5.66
	65.4	0.78	1.19	64.93	0.72
<b>Average</b>			3.68		5.66

The predicted  $f_{cu}$  values of RAC are all lower than that of the NAC. It is slightly

different from the experimental results that the strength values of RAC made with high quality RA are comparable with that of the NAC. The differences may be due to the lack of data related to high strength concrete in constructing the networks model of ANN<sub>16</sub>- $f_{cu}$ .

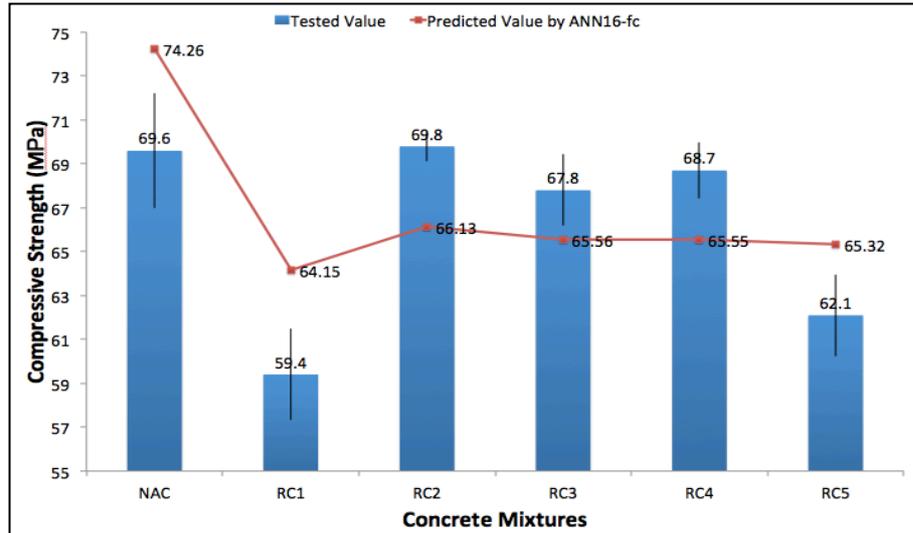
**Table 7-10 - Predicted results of ANN<sub>16</sub>- $f_{cu}$  in Case III**

	Experimental results			Predicted results	
	$f_{cu}$ (MPa)	SD (MPa)	COV (%)	$f'_{cu}$ (MPa)	Error(%)
<b>Case III</b>	54.4	1.66	3.05	53.15	2.30
	54.4	1.01	1.86	52.37	3.73
	54.9	0.51	0.93	51.57	6.06
	52.5	2.87	5.47	51.19	2.50
	54.2	2.39	4.41	52.47	3.20
	52.3	1.35	2.58	51.73	1.09
	46.9	2.52	5.37	51.33	9.45
	50.2	1.83	3.8	53.36	6.30
	50.3	0.55	1.1	49.27	8.02
	49.2	0.25	0.5	45.80	6.91
	48.4	0.31	0.64	48.83	0.88
	44	0.79	1.83	44.73	1.66
	47.5	0.26	0.54	48.16	1.40
	42.4	2.64	6.88	43.71	3.09
	46.7	1.88	3.79	47.12	0.90
	41.1	0.72	1.75	42.21	2.71
	49.1	1.91	3.89	48.44	1.34
	44.7	1.36	3.04	43.71	2.21
	50.7	2.03	4.01	47.53	6.24
	39.9	0.63	1.58	42.37	6.19
<b>Average</b>			2.85		3.51

***Application of ANN<sub>16</sub>- $f_{cu}$  to Case II***

Figure 7-12 gives the detailed comparison of the predicted and the tested results in Case II. The errors of most of the predictions are in the ranges of the standard deviation (SD). The situation is more obvious for the predictions of NAC, as shown in Table 7-9.

As shown in the Figure, it is noted that with the decrease in W/C, the predicted  $f_{cu}$  values of all the concrete mixtures, prepared by either NA or RAs, increase gradually. The predictions are consistent with the trend of the experimental test values. The predictions of C30 concrete are generally slightly lower than the test results, and the increase of the predicted values for RAC is slower than that NAC with the increase of the target strength. The predicted strength of C80 concrete made with NA2 and RAs are lower than the experimental tested values. This can be also attributed to the lack of data related to high strength concrete in constructing the networks model  $ANN_{16-f_{cu}}$ .



**Figure 7-11 - A comparison of the predictions by ANN<sub>16</sub>-f<sub>cu</sub> with the test results in Case I**

### *Application of ANN<sub>16</sub>-f<sub>c</sub> to Case III*

The performances of the networks in Case III (Table 7-10) are shown in Figure 7-13 - Figure 7-15. For NAC made with 0-15% NA replaced by crushed clay bricks or tiles, a reduction of compressive strength with the increase of the replacement ratio can be noticed in Figure 7-13. The general trend is similar to those of the experimental results.

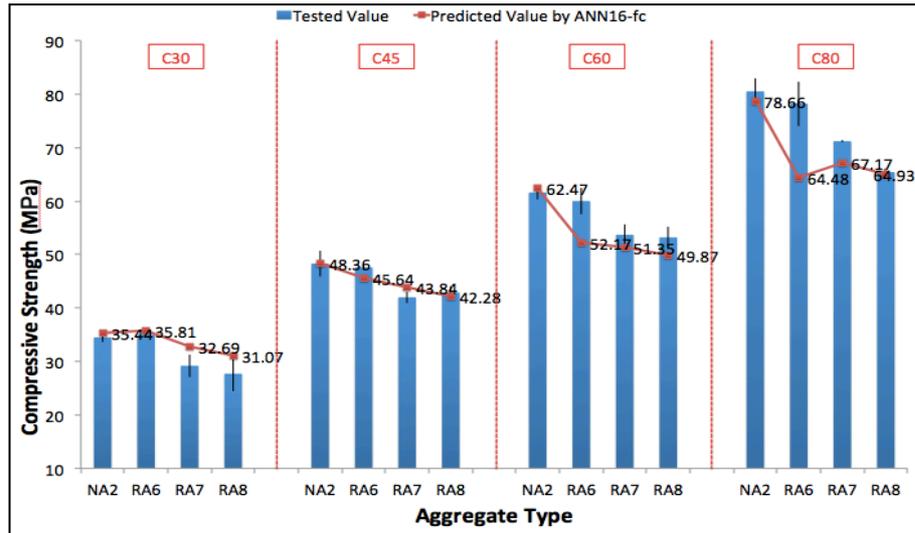


Figure 7-12 - A comparison of the predictions by ANN<sub>16</sub>-f<sub>cu</sub> with the test results in Case II

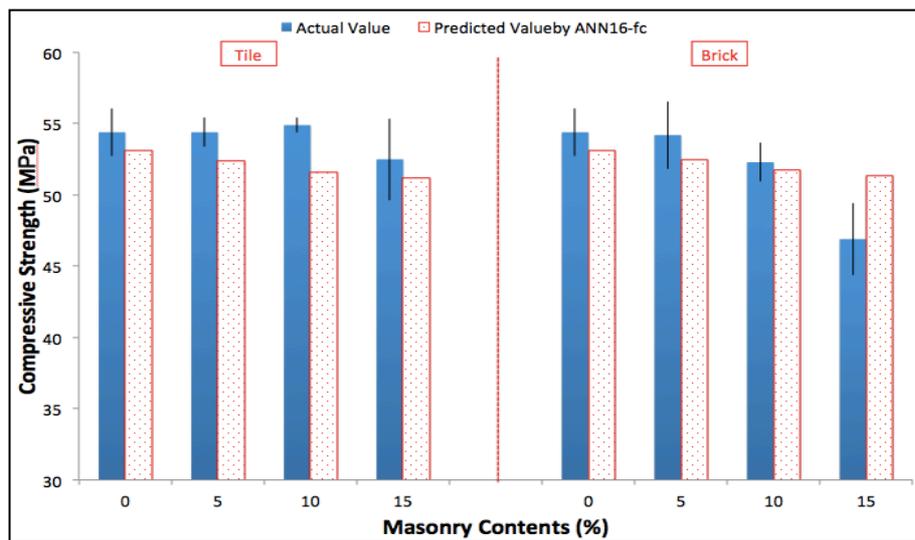
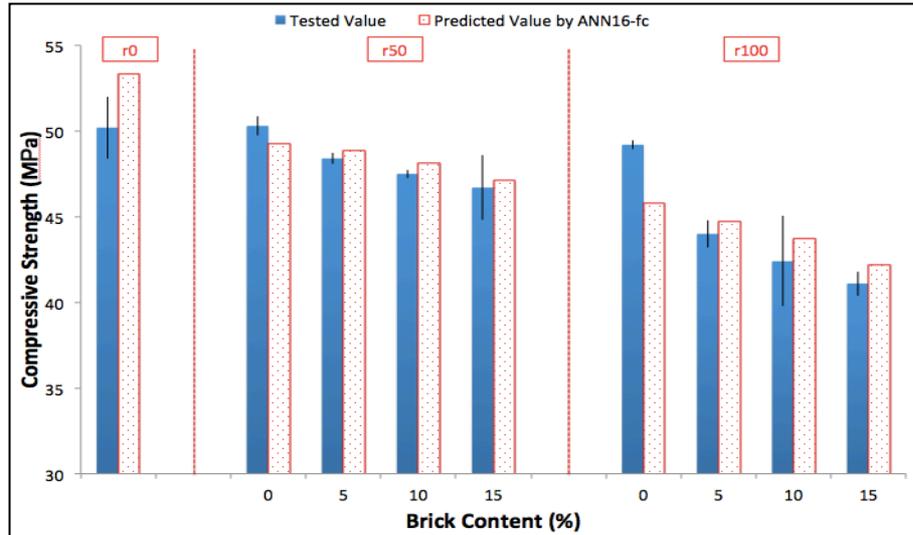


Figure 7-13 - f<sub>cu</sub> predictions by ANN<sub>16</sub>-f<sub>cu</sub> for NAC made with added masonry



**Figure 7-14 -  $f_{cu}$  predictions by ANN<sub>16</sub>- $f_{cu}$  for RAC made with crushed clay bricks**

For RAC made with RA partially replaced by crushed clay bricks or tiles, as shown in Figure 7-14 and Figure 7-15, respectively, the predicted results show a reduction in  $f_{cu}$  of RAC with an increase of the replacement ratio. The reduction is more obvious when 100% RA is used as the coarse aggregate. These predicted trend matches well with the experimental results.

In summary, similar to ANN<sub>16</sub>- $E_c$  for elastic modulus, ANN<sub>16</sub>- $f_{cu}$  can also perform well in predicting the  $f_{cu}$  values of all the collected datasets and the author's own experimental data in the Cases.

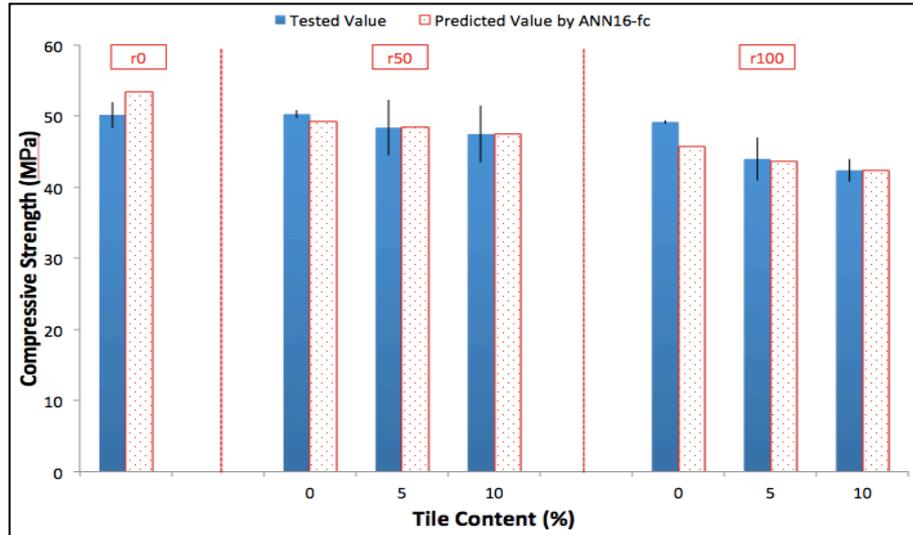


Figure 7-15 -  $f_{cu}$  predictions by ANN<sub>16-f<sub>cu</sub></sub> for RAC made with crushed files

## 7.4 SENSITIVITY ANALYSIS

### 7.4.1 Introduction

Following the review of literatures in Section 2.4.4, sensitivity analyses are conducted to determine the best combination of factors for each model. As there are two input variables used to represent the characteristic of cement type, so the two variables are considered as a factor. To ease the analysis, the concrete mix proportions (5 variables) are designated as “certainties”, while the other factors (10 variables) are named as “uncertainties”. For the analysis, two approaches are adopted as shown in Figure 7-16.

- Factor addition method (FAM). This method is carried out to examine whether the selection of the “uncertainties” is reasonable. Networks (ANN<sub>5</sub>) with

only "certainties" (5 variables) as input variables are first trained, then the resulted error is compared with that generated from the models when each uncertainty is sequentially added to the "certainties". The larger the reduction in the error value, the more important role played by the respective "uncertainty", and vice versa.

- Factor reduction method (FRM). After applying the FAM, the uncertain factors that cannot reduce the error value of ANN<sub>5</sub> are removed, and the remained "uncertainties" are then assessed to determine their importance to the output according to FRM. Using FRM, the networks with each "uncertainty" removed from the inputs of ANN<sub>16</sub>-f<sub>cu</sub> or ANN<sub>16</sub>-E<sub>c</sub> are trained, and the resulted MAPE values are compared with that of ANN<sub>16</sub>-f<sub>cu</sub> or ANN<sub>16</sub>-E<sub>c</sub>. For each uncertain factor tested, the smaller the increase in the error value means the more important the factor is in the model, and vice versa. Then the least important factor is removed from the input variables to construct a new model (ANN<sub>14</sub>). This iteration is used continuously for each uncertain factor till only the "certainties" are left. In this way, the significance of each "uncertainty" to the output can be determined.

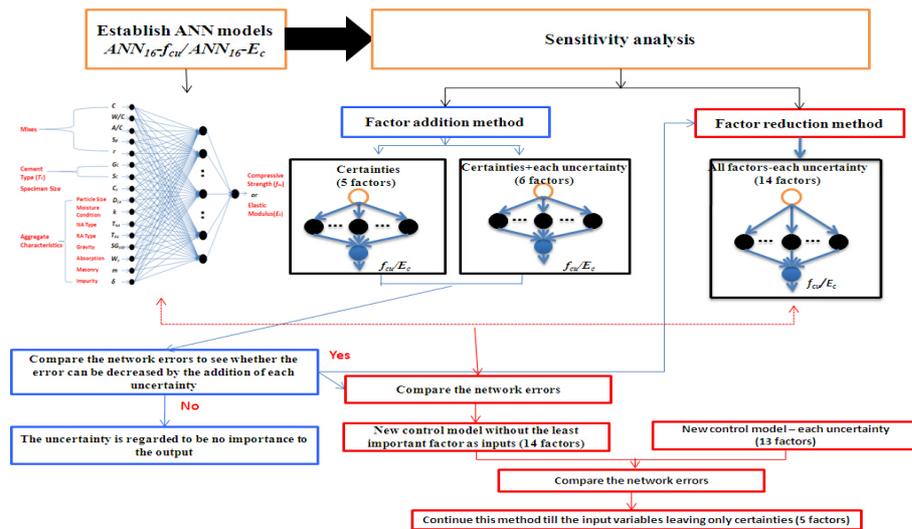


Figure 7-16 - Flow chart of sensitivity analysis

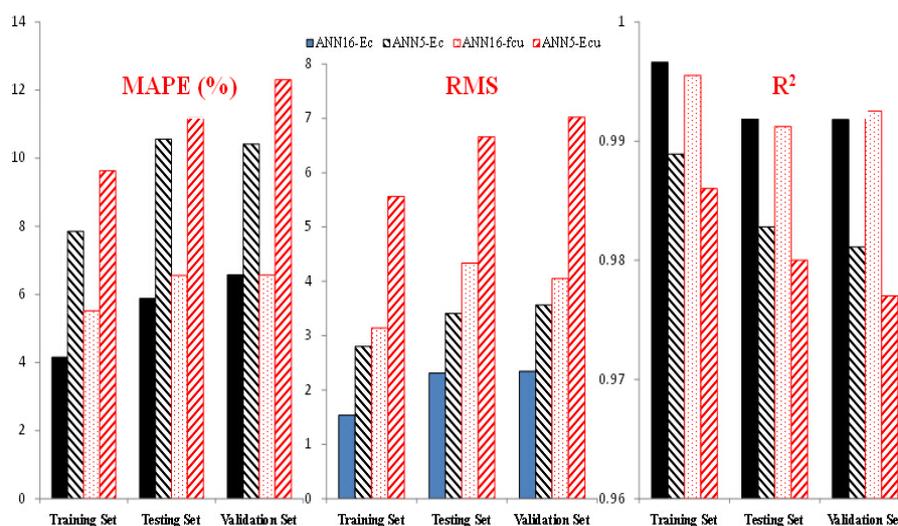
Considering that the predicted results of networks may change slightly each time even with the same model, the networks is trained 5 times and the average values of MAPEs of the testing set and the validation set are used as the final indicator of the network error.

## 7.4.2 Results and discussion

The performance of the constructed ANN models in predicting  $f_{cu}$  ( $ANN_{16}-f_{cu}$ ) and  $E_c$  ( $ANN_{16}-E_c$ ) of RAC, respectively, as well as a comparison relative to the models ( $ANN_5-f_{cu}$ , and  $ANN_5-E_c$ ) with only certainties as input variables, is shown in Table 7-11 and Figure 7-17.

**Table 7-11 - Performance of ANN models**

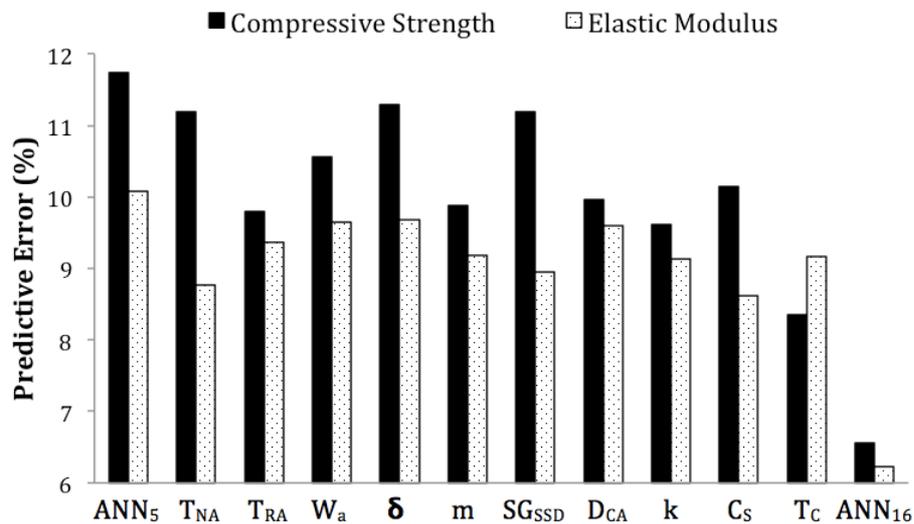
Sets	Model	$R^2$	RMS	MAPE (%)	Model	$R^2$	RMS	MAPE (%)
Training		0.995	3.14	5.518		0.999	1.53	4.152
Testing	$ANN_{16-f_c}$	0.991	4.33	6.558	$ANN_{16-E}$	0.992	2.31	5.88
Validation	$u$	0.992	4.04	6.562	$c$	0.991	2.34	6.574
n		5	8			8	6	
Training		0.986	5.56	9.624		0.988	2.80	7.845
Testing	$ANN_{5-f_{cu}}$	0.98	6.65	11.188	$ANN_{5-E_c}$	0.982	3.41	10.555
Validation		0.977	7.01	12.294		0.981	3.56	10.408
n			7			1	5	



**Figure 7-17 - Performance of the constructed ANN models with all 16 variables and only “certainties” (5 variables) as inputs**

As can be seen from Table 7-11, the indexes shown in the testing and validation sets prove that the constructed ANN models ( $ANN_{16-f_{cu}}$  and  $ANN_{16-E_c}$ ) both have strong generalization ability, and are capable of predicting the compressive

strength and elastic modulus of RAC made with RAs from different sources accurately. However, when only mixes of RAC are used as input variables, it is nearly impossible for the networks (ANN<sub>5</sub>-f<sub>cu</sub> and ANN<sub>5</sub>-E<sub>c</sub>) to convergence, and indicators data are also significantly worse than those of the control models (ANN<sub>16</sub>-f<sub>cu</sub> and ANN<sub>16</sub>-E<sub>c</sub>), with the MAPE values all exceed 10%. This also proves the importance of the uncertain factors on the properties of RAC.



**Figure 7-18 - Influence of each “uncertain” on the properties of RAC relative to models with only “certainties” as inputs**

The results of FAM, as shown in Figure 7-18, indicate that the addition of all uncertain factors are useful to reduce the predictive error of the networks (ANN<sub>5</sub>). Among all the uncertainties, cement type and specimen size are the most effective factor for improving the performance of ANN<sub>5</sub>-f<sub>cu</sub> and ANN<sub>5</sub>-E<sub>c</sub>, with a reduction of the MAPE values to 8.36% and 8.62%, respectively. However, their

performance can still not be 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 relative importance of each uncertainty.

**Table 7-12 - Errors of network for  $f_{cu}$  measured by FRM (%)**

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

The detailed results of each of the network for  $f_{cu}$  and  $E_c$  by adopting FRM can be noticed in Tables 7-12 and 7-13, respectively. For  $f_{cu}$ , as shown in Table 7-12, the error of network with all factors as input variables ( $ANN_{16-f_{cu}}$ ) is about 6.56%. When each “uncertainty” is sequentially excluded from the input variables, the networks error increases slightly between 7.15% and 8.02%, among which the least rise belongs to the combination without NA type as inputs, so the NA type is regarded as the least important factor to the  $f_{cu}$  of RAC.

**Table 7-13 - Errors of network for  $E_c$  measured by FRM (%)**

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

For Tables 7-12 and 7-13, figures with \* represent the MAPEs of the control ANN model ( $ANN_{16}-f_{cu}$  or  $ANN_{16}-E_c$ );

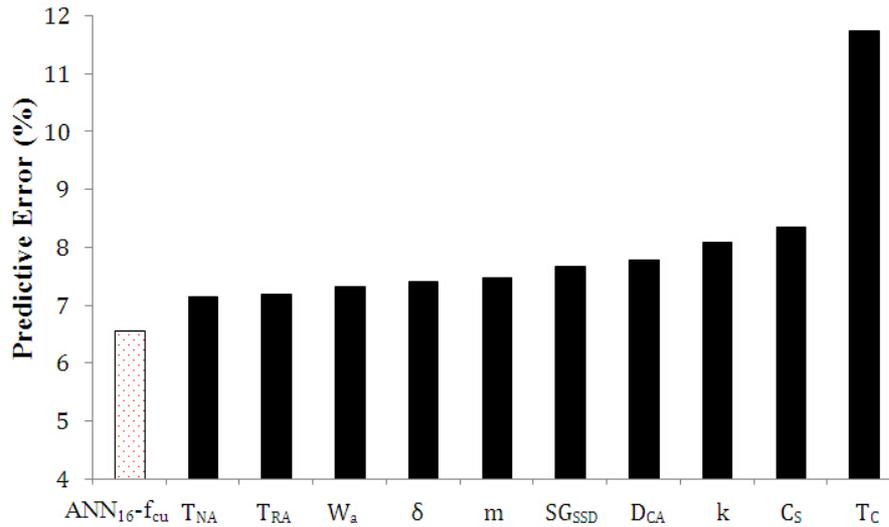
Other figures represent the MAPEs of the networks when the factors, both in the corresponding column and before the corresponding rows, were removed from the inputs of  $ANN_{16}$ ;

Figures in bold mean that the MAPE of the networks was the lowest among the corresponding row.

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

Using this method, the “uncertainties” are removed based on their impact on the  $f_{cu}$  in descending order. As shown in Figure 7-19, the orders of importance of the “uncertainties” are as follows:

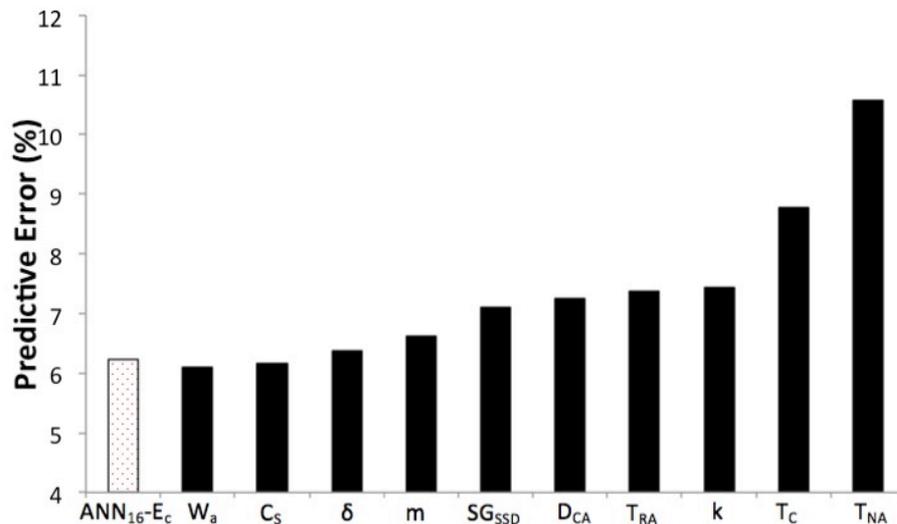
Cement type - Specimen size - Aggregate moisture - Particle size - Specific gravity - Masonry content - Impurity content - Water absorption - RA type - NA type.



**Figure 7-19 - Errors of network for  $f_{cu}$  with the remove of “uncertainties” sequentially according to their importance**

It can be concluded that the physical properties of the aggregate, such as aggregate type, water absorption and specific gravity, impurity and masonry content, play relatively minor roles in determining the  $f_{cu}$  of RAC compared with other “uncertainties” like cement type, specimen size, aggregate moisture and particle size.

While for the elastic modulus (Table 7-13), the case is slightly different. Firstly, relative to ANN<sub>16</sub>-E<sub>c</sub>, the error of the network without using water absorption in the inputs drops slightly to about 6.09%. This may be due to that specific density 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 E<sub>c</sub> than that in the f<sub>cu</sub> prediction.



**Figure 7-20 - Errors of network for E<sub>c</sub> with the removal of “uncertainties” sequentially according to their importance**

Besides, the orders of importance of other “uncertainties” are similar to that for the f<sub>cu</sub> (Figure 7-20), and they are:

NA type - Cement type -Aggregate moisture - RA type - Particle size - Specific gravity - Masonry content - Impurity content - Specimen size - Water absorption.

However, some of the uncertain factors are generally kept constant when using RA to produce new concrete in practice, such as the cement type, the specimen size, the types of NA and RA, and the aggregate particle size. So it may be more important to determine the relative importance of the rest of the uncertain factors. It can be noted from Figures 7-19 and 7-20 that, the order of importance of these uncertain factors, is exactly the same both for the compressive strength and the elastic modulus, as follows :

Aggregate moisture - Specific gravity - Masonry content - Impurity content - Water absorption.

This may be the reason why many researchers choose to model the elastic modulus of RAC by using the corresponding compressive strength value.

It can also be concluded that, when designing mix proportions of RAC in practice, better RAC mechanical properties may be achieved by using RA with an appropriate moisture condition, higher density, lower masonry and impurity contents, and lower water absorption values.

To sum up, it is better to use all the selected uncertain factors, together with certainties, to construct the ANN models to predict the compressive strength/elastic modulus of RAC made with RAs from different sources, since the removal of any certain factor will cause the use of an incomplete mix proportion, while the removal of any uncertain factor may lead to an increase in the predicted error (except  $W_a$  for ANN- $E_c$ ). Besides, the importance of each uncertain factor to the compressive strength prediction is also not completely similar to that to the elastic modulus. This can be used to explain why many established correlation 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 analysis is slightly different due to the following reasons: (1) FAM is conducted according to ANN<sub>5</sub>- $f_{cu}$ /ANN<sub>5</sub>- $E_c$ , while FRM is based on ANN<sub>16</sub>- $f_{cu}$ /ANN<sub>16</sub>- $E_c$ ; (2) FAM is mainly used 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 related, such as factors relating to aggregate characteristics. So it is necessary to further examine the importance of each aggregate characteristic to the properties of RAC.

## **7.5 SUMMARY**

- The constructed ANN models ( $ANN_{16-f_{cu}}$  and  $ANN_{16-E_c}$ ) both have strong generalization ability, and are able to predict the  $f_{cu}$  and  $E_c$  of RAC made with RAs from different sources accurately, with the MAPE values all in the range of 5.8%-6.6%.
- The generalization capacities of both  $ANN_{16-f_{cu}}$  and  $ANN_{16-E_c}$  have been proven by the researcher's own experimental results (Case I - Case III). Compared to the predicted results based on the traditional regression analysis, the ANN method can produce better predictions.

- The results of the factor addition method demonstrate that the addition of each “uncertainty” in this study is useful to reduce the predictive error.
- The factor reduction method is able to further assess the importance of each uncertain factor in the ANN model. For  $f_{cu}$ , cement type and specimen size are the most important factors, and the aggregate moisture content is the most influential factor amongst all aggregate characteristics. While for  $E_c$ , although cement type still plays an important role, aggregate characteristics like NA type and RA type should also be taken into account.
- After carrying out the sensitivity analysis, the networks for  $E_c$  can be used to provide better predicting when water absorption of coarse aggregate is removed from the input variables.

# **CHAPTER 8: CONCLUSION AND RECOMMENDATIONS FOR FUTURE WORK**

## **8.1 CONCLUSION**

A comprehensive study of the use of artificial neural networks for predicting the compressive strength and elastic modulus of recycled aggregate concrete made with different types of recycled aggregates is presented in this thesis. Besides the literature review, the research has been divided into three parts: (1) experimental investigations of the properties of several types of recycled aggregates and the prepared recycled aggregate concrete (Chapter 3 - Chapter 4); (2) examination of the application of established empirical equations in predicting the compressive strength and elastic modulus of recycled aggregate concrete (Chapter 5); (3) the trial of using artificial neural networks to model the properties of recycled aggregate concrete based on selected published literatures (Chapter 6); (4) through collecting data from large number of different published literatures worldwide as the sample datasets, networks models with generalization abilities are constructed for predicting the compressive strength and elastic modulus of recycled aggregate concrete. Sensitivity analyses are also made to examine the

importance of the selected factors and determine which combination of factors could be used to construct the best model. (Chapter 7);

The following conclusions can be drawn from the present study:

### **8.1.1 Experimental test results**

#### ***Properties of RAC made with RAs derived from laboratory prepared concrete cubes with different compressive strength (35-85 MPa):***

- The test results of physical and mechanical performance indicate that the properties of RA is generally poorer than that of natural aggregate, RA2 and RA1 have the best and worst performance among the total five RAs, respectively.
- The experimental results on compressive strength and splitting tensile strength indicate that RA2-RA4 can be used to fully replace NA to produce high strength concrete with mechanical properties comparable to the concrete that are made with NA.
- The test results on elastic modulus point that the elastic modulus values of concrete made with recycled aggregates of different qualities are lower than that of the corresponding natural aggregate concrete.
- In all the RAC, the resistance to chloride ion penetration of RAC3 is the best, while the resistance ability of RAC1 is the worst.

#### ***Properties of RAC made with RAs derived from 3 different sources and crushed by different methods:***

- The mortar contents attached to RAs obtained from different sources vary greatly, and this may be related to original mortar content and the degree of prior mechanical crushing received.
- The hardened density of RAC is generally lower than that of NAC, and has a good correlation with the specific gravity of the RAs used.
- The experimental results on compressive strength, splitting tensile strength and elastic modulus indicate that RA of good quality can be used to fully replace NA to produce concrete with mechanical properties comparable to concrete that made with NA.
- The test results on the resistance to chloride ion penetration and drying shrinkage of concrete show that the durability properties of the concrete made with a good quality RA can be comparable to those made with NA.

***Properties of RAC made with RAs contained different amounts of added masonries***

***(clay bricks or tiles):***

- The physical and mechanical properties of crushed clay bricks and tiles are much weaker than those of NA, and are even cannot be comparable with those of RA, which limit the use of RA that contains high percentage of masonries in concrete.

- Due to the lower specific gravity of brick and tile, the hardened density of the concrete made with brick or tile addition is lower than the corresponding NAC.

### **8.1.2 Predicted properties of RAC by established relationships**

- For concrete made with NA and RAs from different sources, the established relationships between the elastic modulus and compressive strength show that the elastic modulus value is difficult to be expressed effectively by only the corresponding strength value. ACI 318-95 and BS EN 1992-1-1 are also proved to overestimate the elastic modulus of RAC.
- The empirical equations previously developed by different researchers expressing elastic modulus as a function of the corresponding compressive strength cannot be used to provide a general prediction due to the diverse nature of RAs and different parameters that might have been considered in different previous studies.
- There are also limitations on the use of the relationship to predict compressive strength and elastic modulus based on the water absorption and specific gravity of RA.

### **8.1.3 Use of ANN in RAC**

- When using compressive strength of RAC as the only input variable to model the corresponding elastic modulus by ANN, the performance in the testing and validation sets is not very well.
- When more parameters related to the mix proportions and aggregate characteristics are included as the input variables, the constructed models can produce better predictions.
- However, ANN model based on only one source of dataset is very difficult for application in predicting the corresponding performance of another dataset due to the limitations of ANN and the dataset itself.

For ANN models constructed by using data collected from many international literatures as sample data, the following conclusions can be drawn:

- The constructed ANN models ( $ANN_{16-f_{cu}}$  and  $ANN_{16-E_c}$ ) both have strong generalization ability, and is capable of predicting 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 generalization capabilities of both  $ANN_{16-f_{cu}}$  and  $ANN_{16-E_c}$  are proved by the author's own experimental results (Case I - Case III). The networks can produce better predictions.

- The results of the Factor Addition Method demonstrate that the addition of each uncertain factor in this study is helpful to reduce the predictive error of both networks for compressive strength and elastic modulus.
  
- The results of the Factor Reduction Method can further determine the importance of each uncertain factor to the performance of RAC predicted by ANN. For compressive strength, cement type and specimen size are the most important parameters, and aggregate moisture condition is the most influential parameter in all aggregate characteristics. While for elastic modulus, although cement type still plays an important part, aggregate characteristics like NA type and RA type also cannot be ignored.

## **8.2 RECOMMENDATIONS FOR FUTURE WORK**

Although it has been demonstrated that ANN is capable of predicting the compressive strength and elastic modulus of recycled aggregate concrete made with recycled aggregates derived from different sources, it is still of interest to know whether other properties of RAC like workability, durability and deformation properties (as shown in Figure 8-1) can be also modeled by ANN.

Also, an ANN based expert system, as shown in Figure 8-2, may be developed to provide guidance in designing the mix proportions of RAC. Besides, the ANN method can be also used in some other areas of RAC, such as in concretes made also with recycled fine aggregates or mineral admixtures.

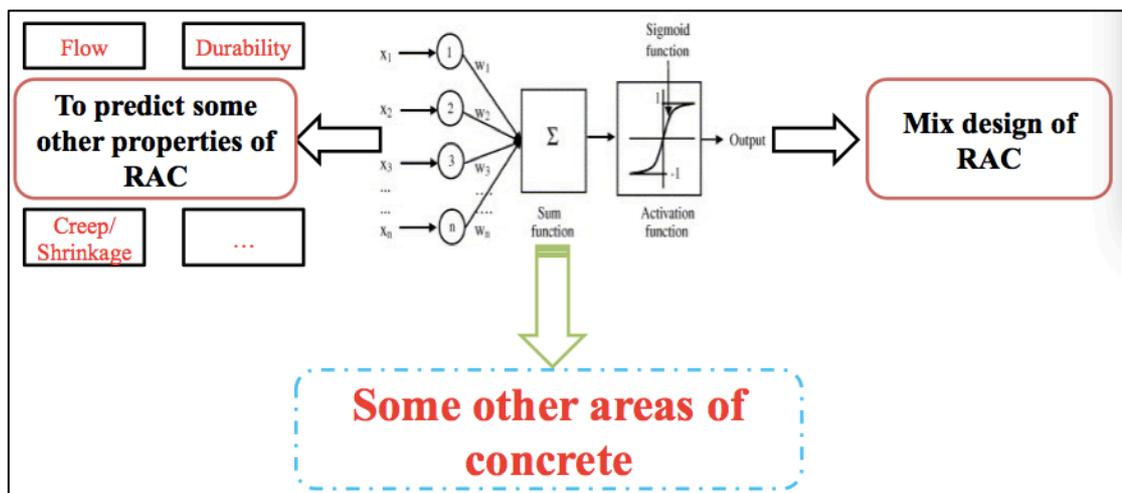


Figure 8-1– Proposed use of ANN method in future studies

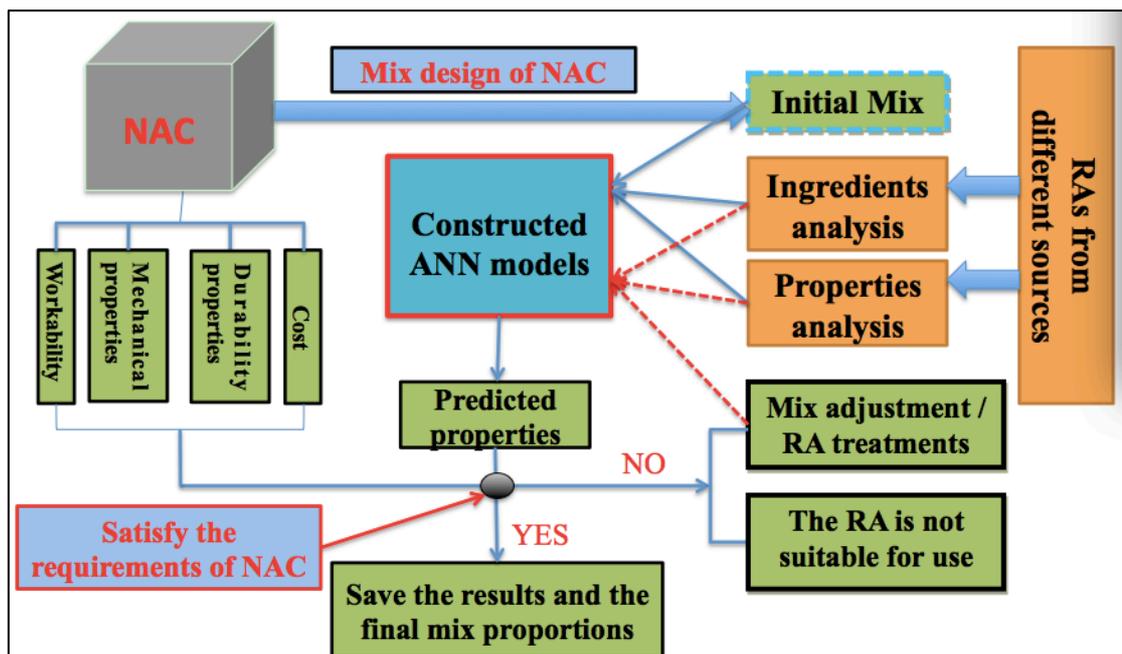


Figure 8-2– Proposed expert system for mix design of RAC

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