Orthogonal tests investigation into hybrid fiber-reinforce recycled aggregate concrete and convolutional neural network prediction

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ABSTRACT

An orthogonal test method was used to do sensibility analysis on the compressive strength and splitting strength of hybrid fiber-reinforced recycled aggregate concrete (HyFRAC). And a prediction model of compressive strength of HyFRAC based on Convolutional Neural Network (CNN) was proposed. The results show the ratio of recycled brick aggregate (RBA) to recycled concrete aggregate (RCA) has been proved the greatest influence on the compressive strength and splitting tensile strength of HyFRAC, followed by the water reducing agent content, finally the ratio of glass fiber (GF) to polypropylene fiber (PF). When RBA/RCA = 2/8, GF/PF = 7/3, and water reducing agent content is 0%, the compressive strength and splitting tensile strength of HyFRAC are the highest. According to JG/T110-2011, when RBA/RCA ≤ 6/4 and water reducing agent content ≥ 0.4%, the HyFRAC slump meets the 50m pumping height requirement; when RBA/RCA ≤ 6/4 and water reducing agent content ≥ 0.6%, the HyFRAC slump meets the 100m pumping height requirement. Compared to back propagation (BP) neural network model and multiple linear regression model, CNN model is more efficient in estimating the compressive strength of HyFRAC. The average relative errors and max relative errors of CNN model are 1.98% and 4.12%, respectively.

1. Introduction

Concrete is widely used in buildings, bridges and roads. At the same time, some old buildings, bridges and roads were demolished. It is estimated that more than 18 billion tons of concrete waste are produced every year in China (Hua and Yuanfeng 2019), which will be beneficial to protect the environment if can be recycled. Whereas the concrete rubble from demolished building usually contain not only crushed concrete but also crushed brick (Yang, Du, and Bao 2011). The concrete by using crushed brick as aggregate is called recycled brick aggregate concrete (RBAC), and the concrete by using crushed concrete as aggregate is called recycled concrete aggregate concrete (RCAC). RBAC and RCAC are called recycled aggregate concrete (RAC). And limited to the cost and the technology, it is difficult to separate recycled concrete aggregate (RCA) and recycled brick aggregate (RBA) from construction waste. However, the quality of RAC is dependent on recycled aggregate (RA) (Zongping, Chunheng, and Dingyi, Jing, and Bo 2017; Yuanxin, Qiuyi, and Gongbing, and Qianqian 2018), and previous studies about RAC never focus on the RBA/RCA ratio. Therefore, it is necessary to study the performance of RAC with different RBA/RCA ratios.

The mechanical properties of RAC were widely reported in recent years (Younis, Amin, Ahmed, and Maruf 2020; Wang, Xie, He, Sun, Yang, and Li 2020; Rashid, Tariq, and Shaukat 2019; Zhenxuan, Shaohua, Mosallam, Shuo, and Wenxian 2020). (Chaoan, Cong, Geng, Xiaozhen, Zhiiwu, and Liqin 2018) investigated that the effect of the replacement of natural aggregate (NA) with either RCA or RBA on the compressive strength of concrete. The results showed that with the increase in replacement of the RA/NA ratio, the compressive strength of concrete decreases gradually. Silva, Brito, and Dhir 2018 investigated that when the coarse aggregate, fine aggregate and the combined aggregate are fully substituted by RBA, the compressive strength decreases by 35%, 30% and 40%, respectively. Similar investigations into RBAC can be found in review articles by (Yang, Du, and Bao 2011) and (Pitaruch, Reig, Tomás, and López 2017) respectively. Chaoan, Cong, Geng, Xiaozhen, Zhiiwu, and Liqin 2018 investigated RCA or RBA on the compressive strengths of concrete. It was found that RCAC has better performance than RBAC. Furthermore, Bui, Satomi, and Takahashi (2017) investigated the mechanical properties of RAC with different RBA/RCA ratios. The results showed that the mechanical properties of RAC decrease with the increase of RBA/RCA ratio.
According to research above mentioned, it is found that either RCA or RBA may lead to lower concrete performance such as low compressive strength and poor durability. It was reported that fibers such as steel fiber and polypropylene fiber used as reinforcing materials could significantly improve the performance of concrete (Shah and Ribakov 2011; Lee, Oh, and Cho 2015; Qin, Zhang, Chai, Xu, and Li 2019; Ju, Wang, Liu, and Ma 2018; Wang, Ju, Shen, and Xu 2019; Hanumesh, Harish, and Venkata Ramana 2018). Moreover, some researches about hybrid fiber used in concrete was widely reported, and the results showed that hybrid fiber reinforced concrete could result in superior composite performance compared to single fiber reinforced concrete (Lawler, Zampini, and Shah 2016; Guler and Yavuz 2019; Guler, Yavuz, and Aydin 2019; Guler, Yavuz, Korkut, and Ashour 2019; Yao, Li, and Wu 2003). Jen, Trono, and Ostertag 2016 pointed out that hybrid fiber reinforcement was shown to provide an improvement to the phenomena of internal confinement and tension stiffening, for compression and tension loading, respectively, which allow for a significantly improved post cracking response. Guler, Ker, and Akbulut 2021 investigated the effects of macro steel, forta-ferro and polyamide synthetic fibers on the slump, compressive, splitting tensile, flexural strength, flexural toughness and rebound rate of wet-mix shotcrete. Caggiano, Volino, Lima, Martinelli, and Pepe 2017 found that industrial fibers can be replaced by an equal amount of recycled ones without a significant decay in the relevant mechanical properties, provided that the recycled fibers present adequate geometrical characteristics. Prathipati and Rao 2020 found that short length glass fibers and short length steel fibers have exhibited significant improvement in flexural strength and peak stress. Barhum and Mechtcherine 2012 reported that the first-crack stress value of specimens increased by two to three times due to the addition of 1.0% by volume carbon fiber and glass fiber (GF). Mehmet (Arslan 2016) pointed out that the splitting tensile and flexural strength of basalt fiber reinforced concrete and GF reinforced concrete were improved with fiber content increases, whereas high fiber content will lead to a slight decrease in flexural strength. The high water absorption of RA and the addition of fiber lead to the decrease in slump of RAC. In order to improve the slump of RAC, water reducing agent can be added.

Multiple linear regression is a very good tool to predict concrete strength, but sometimes multiple linear regression may produce large prediction error (Janani and Santhi 2018; Saravanan Kumar 2018). In recent years, the emergence of back propagation (BP) neural network provides a new method for multivariable prediction. Subhedar established multiple linear regression model and BP neural network model with concrete components as variables respectively. The results showed that BP neural network model had higher prediction accuracy for concrete compressive strength than multiple linear regression model. Similar studies can be found in some literatures (Khadem and Behfarnia 2016; Li and Wang 2019). After that, Tu, Liu, Zhou, and Li 2020 optimized the BP neural network, which had better prediction stability. However, Jinjun, Zongping, Xiao, Demartino, and Junhua 2017 proposed multiple nonlinear regression (MNR) and artificial neural network (ANN) methods to predict the mechanical properties of RAC. The results show that the proposed MNR and ANN methods can predict the mechanical properties of RAC more accurately than the existing models. Compared with other machine learning systems, TensorFlow, a machine learning system developed by Google, is faster, more intelligent and more flexible (Rampasek and Goldenberg 2016; Abadi 2016). Convolutional neural network (CNN) based on TensorFlow platform has higher prediction accuracy and prediction speed than traditional BP neural network (Shanjie and Shizhe). Several studies (Deng, He, Zhou, Yu, Cheng, and Wu 2018; Shuangxi, Wei, and Shunai 2019) used CNN for predicting the mechanical properties and durability of different types of concrete. These studies showed that the prediction results of CNN were more accurate and closer to actual values.

In this paper, the orthogonal test was used to do sensibility analysis on the compressive strength and splitting tensile strength of hybrid fiber-reinforced recycled aggregate concrete (HyFRAC). Factors to be considered including the RBA/RCA ratio, the ratio of glass fiber (GF) to polypropylene fiber (PF) and the water reducing agent content. And a prediction model of compressive strength of HyFRAC based on CNN model was proposed. The results showed that the RBA/RCA ratio has been proved the greatest influence on the compressive strength and splitting tensile strength of HyFRAC, followed by the water reducing agent content, finally the GF/PF ratio. The CNN model established in this paper is efficient in estimating the compressive strength of HyFRAC, as compared to the BP neural network model and multiple linear regression model, which provides a new idea to predict the compressive strength of HyFRAC.

2. Test program

2.1. Purpose of the test

Orthogonal test design is an efficient, fast and economical test design method. For example, in a three-factor and four-level test, according to the requirements of comprehensive test, $3^4 = 81$ combinations of test must be carried out. If the test is arranged according to $L_{16} (4^3)$ orthogonal table, only 16 tests are needed, which obviously reduces the workload greatly. Therefore, orthogonal test design has been
widely used in many fields. HyFRAC was taken as the research object in this study. The influence of the RBA/RCA ratio, the GF/PF ratio and the water reducing agent content on the strength of RAC was studied by using the orthogonal test design method. The sensitivity of various factors on the compressive strength and splitting tensile strength of HyFRAC was analyzed. Finally, the best mix proportion was found.

2.2. Materials
The materials used in the present experimental studies are as follows. The ordinary Portland cement with a compressive strength of 42.5 MPa at 28 days. The fine aggregate is ordinary river sand with fineness modulus of 2.76 and water content of 0.1%. The basic properties of RBA and RCA are shown in Table 1, and the gradation curve is shown in Figure 1. Two kinds of fibers were used as shown in Figure 2. One is the PF and the other is GF. The former has a diameter of 0.031 mm, a length of 19 mm, and a tensile strength of 400 MPa. The latter has a diameter of 16 mm, a length of 24 mm, and a tensile strength of 600 MPa. The water reducing agent is the type of SK-3 produced by Chinese Academy of Water Sciences.

2.3. Orthogonal text design
The target concrete grade of this study is C30. According to JGJ55-2011, the content of aggregate, sand, cement, water and fly ash can be calculated, and the RBA/RCA ratio is 8/2, 6/4, 4/6 and 2/8, respectively. Guler, Yavuz, and Aydin 2019 pointed out that the reasonable volume fraction of hybrid fiber was between 0.5% and 1.5%. TAN Hongxia et al. (Hongxia,

Table 1. Physical properties of RA.

| Aggregate type | Apparent density/kg/m³ | Bulk density/kg/m³ | Crushing index/% | Water absorption/% |
|----------------|------------------------|--------------------|------------------|-------------------|
| RBA            | 1853                   | 1012               | 21               | 18.5              |
| RCA            | 2415                   | 1336               | 14.3             | 6.2               |

Figure 1. RA gradation curve. (a) RCA (b) RBA.

Figure 2. PF and GF. (a) PF (b) GF.
Zhifu, and Chaoping, Li, and Jianjian 2011) further pointed out that when the volume fraction of polypropylene fiber was 1%, the mechanical properties of concrete were the best. So 1% volume fraction of hybrid fiber was used in this study, and the GF/PF ratio was 1/9, 3/7, 5/5 and 7/3, respectively. According to the research results of literature (Aijiu, Jing, and Qing 2009), the water reducing agent content of 0%, 0.2%, 0.4% and 0.6% was used, respectively. There were three factors and four levels in this study. According to the orthogonal test table L_{16} (4^3), the orthogonal test was combined.

Three independent factors were studied: (A) the RBA/RCA ratio, (B) the GF/PF ratio, (C) the water reducing agent content. In order to analyze the influence of three factors of the compressive strength and splitting tensile strength of HyFRAC. The table of L_{16} (4^3) was adopted in this test design. The test factors-levels is shown in Table 2, and the mix ratio design is shown in Table 3.

In order to compare the compressive strength and splitting tensile strength of concrete without hybrid fiber, NAC, RCAC and RBAC were also made as comparative tests in this study. The mix proportion is shown in Table 4.

### 2.4. Specimens preparation and testing

RBA and RCA were kept in saturated state before mixing because the best solution for RA is to keep in saturated state in mixing plant procedure. Fine aggregate was used at natural state of moisture. According to Table 3, six specimens were made for each mix proportion, three of which were used for compressive strength test and the other three were used for splitting tensile strength test. All specimens were casted.

| Table 2. Factors-levels. |
|--------------------------|
| Level | Factor A | Factor B | Factor C |
| 1 | RBA/RCA = 8/2 | GF/PF = 1/9 | 0.0% |
| 2 | RBA/RCA = 6/4 | GF/PF = 3/7 | 0.2% |
| 3 | RBA/RCA = 4/6 | GF/PF = 5/5 | 0.4% |
| 4 | RBA/RCA = 2/8 | GF/PF = 7/3 | 0.6% |

| Table 3. The orthogonal test design. |
|-------------------------------------|
| Specimen number | RBA/RCA ratio | GF/PF ratio | water reducing agent content | Water | Cement | Sand | RA | Fiber | Water reducing agent | Fly ash |
|-----------------|---------------|--------------|-----------------------------|-------|--------|-----|----|------|---------------------|--------|
| H-1             | 8:2           | 1:9          | 0%                          | 175   | 400    | 750 | RBA-800 RCA-200      | GF-2.58 PF-8.19 | 0      | 100               |
| H-2             | 8:2           | 3:7          | 0.2%                        | 175   | 400    | 750 | RBA-800 RCA-200      | GF-7.74 PF-6.37 | 0.826  | 100               |
| H-3             | 8:2           | 5:5          | 0.4%                        | 175   | 400    | 750 | RBA-800 RCA-200      | GF-12.9 PF-4.55 | 1.652  | 100               |
| H-4             | 8:2           | 7:3          | 0.6%                        | 175   | 400    | 750 | RBA-800 RCA-200      | GF-18.06 PF-2.73 | 2.478  | 100               |
| H-5             | 6:4           | 1:9          | 0.2%                        | 175   | 400    | 750 | RBA-600 RCA-400      | GF-2.58 PF-8.19 | 0.826  | 100               |
| H-6             | 6:4           | 3:7          | 0%                          | 175   | 400    | 750 | RBA-600 RCA-400      | GF-7.74 PF-6.37 | 0      | 100               |
| H-7             | 6:4           | 5:5          | 0.6%                        | 175   | 400    | 750 | RBA-600 RCA-400      | GF-12.9 PF-4.55 | 2.478  | 100               |
| H-8             | 6:4           | 7:3          | 0.4%                        | 175   | 400    | 750 | RBA-600 RCA-400      | GF-18.06 PF-2.73 | 1.652  | 100               |
| H-9             | 4:6           | 1:9          | 0.4%                        | 175   | 400    | 750 | RBA-400 RCA-800      | GF-2.58 PF-8.19 | 0.826  | 100               |
| H-10            | 4:6           | 3:7          | 0.6%                        | 175   | 400    | 750 | RBA-400 RCA-600      | GF-7.74 PF-6.37 | 2.478  | 100               |
| H-11            | 4:6           | 5:5          | 0%                          | 175   | 400    | 750 | RBA-400 RCA-600      | GF-12.9 PF-4.55 | 0      | 100               |
| H-12            | 4:6           | 7:3          | 0.2%                        | 175   | 400    | 750 | RBA-400 RCA-600      | GF-18.06 PF-2.73 | 0.826  | 100               |
| H-13            | 2:8           | 1:9          | 0.6%                        | 175   | 400    | 750 | RBA-200 RCA-800      | GF-2.58 PF-8.19 | 2.478  | 100               |
| H-14            | 2:8           | 3:7          | 0.4%                        | 175   | 400    | 750 | RBA-200 RCA-800      | GF-7.74 PF-6.37 | 1.652  | 100               |
| H-15            | 2:8           | 5:5          | 0.2%                        | 175   | 400    | 750 | RBA-200 RCA-800      | GF-12.9 PF-4.55 | 0.826  | 100               |
| H-16            | 2:8           | 7:3          | 0%                          | 175   | 400    | 750 | RBA-200 RCA-800      | GF-18.06 PF-2.73 | 0      | 100               |

| Table 4. Mix proportion of concrete without hybrid fiber. |
|----------------------------------------------------------|
| Specimen number | Aggregate type | Dosage of constituent materials in 1 m³ concrete/kg |
|-----------------|----------------|---------------------------------------------------|
| Z-1             | NA             | Water 175 | Cement 400 | Sand 750 | Aggregate 1000 | Fiber 0 | Water reducing agent 1.652 | Fly ash 100 |
| Z-2             | RCA            | Water 175 | Cement 400 | Sand 750 | Aggregate 1000 | Fiber 0 | Water reducing agent 1.652 | Fly ash 100 |
| Z-3             | RBA            | Water 175 | Cement 400 | Sand 750 | Aggregate 1000 | Fiber 0 | Water reducing agent 1.652 | Fly ash 100 |
into 150 mm×150 mm×150 mm cubes, which were cured at room for 28 days, under the condition of the temperature at 20 ± 2°C and relative humidity of 95% according to Chinese criterion GB 50,010–2010 (Ministry of Housing and Urban-Rural Development of the People’s Republic of China 2010). The compressive strength and splitting tensile strength of concrete were measured by TYA-2000 electro-hydraulic machine with 2000 kN axial load capacity as illustrated with Figure 3.

Compressive strength test process:
(1) After 28 days of curing, the specimens were taken out and their side length was measured.
(2) Take the side of the specimen as the upper and lower compression surface, place the specimen on the lower bearing plate, the center of the specimen should be in geometric alignment with the bearing plate, and the upper bearing plate is lowered to just contact the specimen.
(3) Start the instrument, tighten the oil return valve and open the oil delivery valve. Adjust the oil delivery valve to control the loading speed, and the loading speed is displayed in the display panel. According to GB/T50081-2002, the loading speed of concrete with strength grade less than C30 is controlled between 0.3MPa/s-0.5MPa/s; the loading speed of concrete with strength grade greater than or equal to C30 and less than C60 is controlled between 0.5MPa/s-0.8MPa/s; the loading speed of concrete with strength grade greater than or equal to C60 is controlled between 0.8MPa/s-1.0MPa/s.
(4) When the specimen is close to failure and begins to deform rapidly, stop adjusting the oil delivery valve until the specimen is damaged, record the ultimate load of failure, and open the oil return valve to unload the load.

The process of splitting tensile strength test is similar to that of compressive strength test, but there are two differences:
(1) In the splitting tensile strength test, the specimen is put into the splitting fixture and then put on the lower bearing plate for testing.
(2) In the splitting tensile strength test, the loading speed of concrete with strength grade less than C30 is controlled between 0.02MPa/s-0.05MPa/s; the loading speed of concrete with strength grade greater than or equal to C30 and less than C60 is controlled between 0.05MPa/s-0.08MPa/s; the loading speed of concrete with strength grade greater than or equal to C60 is controlled between 0.08MPa/s-0.10MPa/s.

3. Results and discussion
3.1. Damage phenomena
3.1.1. Damage phenomena of RAC without hybrid fiber
Compressive strength test: in the initial stage of loading, vertical micro cracks appeared on the side of concrete cube firstly; with the increase in loading, vertical micro cracks gradually extended; with further increase in loading, micro cracks inside concrete developed, penetrated and formed inclined cracks, the surface concrete began to bulge and peel; when approaching the ultimate loading, inclined cracks penetrated through the whole concrete cube, showing a “X” shaped damage pyramid, as shown in Figure 4(a). Splitting tensile strength test: in the initial stage of loading, there were no cracks on the surface of concrete cube. As the load continued to increase, micro-vertical cracks appeared in the center line of the concrete cube, and
the crack width gradually increased with the increase of loading, and finally the concrete cube was split. The failure of concrete cube was not only the bond failure between RCA and new cement mortar but also the fracture failure of RBA itself, as shown in Figure 4(b).

3.2. Damage phenomena of RAC with hybrid fiber

Compressive strength test: Due to hybrid fibers were uniformly distributed in concrete, the toughness of concrete was enhanced, and the generation and development of cracks were restrained. There was no obvious spalling phenomenon in the whole loading process. Compressive strength failure of concrete approximately belonged to plastic failure, as shown in Figure 5(a). Splitting tensile strength test: Due to hybrid fibers were uniformly distributed in concrete, the failure of concrete cube was not completely split, which was different from that of concrete cube without hybrid fiber. In the vertical cracks, it can be clearly seen that the hybrid fibers were uniformly distributed between the cracks. Splitting tensile strength failure of concrete belonged to plastic failure, as shown in Figure 5(b).

Figure 4. Damage of RAC without hybrid fiber (a) Compression (b) Splitting tension.

Figure 5. Damage of RAC with hybrid fiber (a) Compression (b) Splitting tension.
3.3. Test results and direct analysis

The results of 28d compressive strength and splitting tensile strength of HyFRAC are shown in Table 5. As can be seen that the compressive strength and splitting tensile strength of H-16 are the largest among the 16 groups of specimens. At this time, the RBA/RCA ratio is 2.8, the GF/PF ratio is 7/3 and the water reducing agent content is 0%. The combination of HyFRAC compressive strength and splitting tensile strength reaches the maximum value is A0B0C1. The target strength grade of mix proportion design in this paper is C30. According to Table 5, the compressive strength of all HyFRAC is greater than 30MPa. However, according to Table 6, the compressive strength of RBAC is less than 30MPa. Compared with the concrete without hybrid fiber, the compressive strength and splitting tensile strength of concrete with hybrid fiber are greatly improved. The compressive strength of HyFRAC (A0B0C1) is 1.34 times and 1.64 times of RCAC and RBAC, respectively. The splitting tensile strength of HyFRAC (A0B0C1) is 1.64 times and 1.93 times of RCAC and RBAC, respectively. Therefore, the compressive strength and splitting tensile strength of RAC can be improved by hybrid fiber.

However, it also can be seen from Table 5 that the slump of the specimen corresponding to A0B0C1 is only 55 mm. According to literature (Ministry of Housing and Urban-Rural Development of the People’s Republic of China 2011), when the pumping height is 50 m, the concrete slump shall be 100–140 mm; when the pumping height is 100 m, the concrete slump shall be 150–180 mm. It can be seen from Figure 6 that when RBA/RCA ≤ 6/4 and water reducing agent content ≥ 0.4%, the HyFRAC slump meets the requirement of 50 m pumping height; when RBA/RCA ≤ 4/6 and water reducing agent content ≥ 0.6%, the HyFRAC slump meets the requirement of 100 m pumping height. The slump of HyFRAC increases gradually as the water reducing agent content gradually changes from 0% to 0.6%. However, with the RBA/RCA ratio gradually changes from 2.8 to 8.2, the slump of HyFRAC shows a downward trend, the same trend was reported by (Hongxia, Zhifu, and Chaoping, Li, and Jianian 2011; Aijiu, Jing, and Qing 2009). CHEN Aijiu (Aijiu, Jing, and Qing 2009) pointed out that with the increase of the amount of water reducing agent, the slump increased obviously under the same RA content.

According to Table 4, the compressive strength and splitting tensile strength of each group of specimens were calculated average respectively, as shown in Figure 7 – Figure 8. Figure 7(a) shows that when the RBA/RCA ratio gradually changes from 8/2 to 2/8, the compressive strength gradually increases. It might be due to the strength of RBA is lower than RCA, the
strength of RAC is dependent on RA (Zongping, Chunheng, Dingyi, Jing, and Bo 2017; Yuanxin, Qiyi, Gongbing, and Qianqian 2018). This is in agreement with other literature (Yang, Du, and Bao 2011; Nepomuceno, Miguel, Isidoro, Rui, Catarino, and Jose 2018; Mefteh, Kebaïli, Oucief, Berredjem, and Arabi 2013). The compressive strength of HyFRAC with RBA/RCA = 2/8 increased by 23.56% compared to the specimen with RBA/RCA = 8/2. As can be identified with Figure 8(a), when the RBA/RCA ratio gradually changes from 8/2 to 2/8, the splitting tensile strength first decreases and then gradually increases. This is because the splitting tensile strength has some discreteness, but the overall trend is right. Because the strength of RBA is lower than that of RCA, the splitting tensile strength of concrete should increase with the decrease of the RBA/RCA ratio. The splitting tensile strength of HyFRAC with RBA/RCA = 8/2 increased by 14.87% compared to the specimen with RBA/RCA = 6/4. Significantly, it is identified that the RBA/RCA ratio has a greater influence on the compressive strength and splitting tensile strength of HyFRAC.

As depicted in Figure 7(b), it can be found that the compressive strength gradually increases as the GF/PF ratio gradually changes from 1/9 to 7/3. The compressive strength of HyFRAC with GF/PF = 7/3 increased by 6.01% compared to the compressive strength of HyFRAC with GF/PF = 1/9. The reason is that the GF is well dispersed in the HyFRAC, which can produce the mechanism of energy absorption or bridging action. Under the load, the GF limits the crack development and enhances the compressive strength of the HyFRAC. Whereas, PF has poor dispersion in concrete, which is easily bonded with agglomerates. Similar findings were found in reference (Zhiheng, Ming, and Xisheng, Yihui, and Yanmin 2019; Qian 2015). LV

**Figure 6.** Slump of HyFRAC.

**Figure 7.** The relationship between three factors and compressive strength (a) Factor A (b) Factor B (c) Factor C.
Zhiheng (Zhiheng, Ming, and Xisheng, Yihui, and Yanmin 2019) found that due to the poor dispersion of PF in concrete, the compressive strength of concrete was improved a little only under the condition of low water cement ratio and low content of PF. Figure 8(b) shows that the influence of the GF/PF ratio from 1/9 to 7/3 on the splitting tensile strength is not obvious. The compressive strength of HyFRAC with GF/PF = 3/7 is only 2.86% higher than the compressive strength of GF/PF = 5/5.

As illustrated with Figure 7(c) that the compressive strength gradually decreases as the water reducing agent content gradually changes from 0% to 0.6%. The compressive strength of HyFRAC with the water reducing agent content at 0% is 10.56% higher than that of the water reducing agent content at 0.6%. Figure 8(c) shows that the splitting tensile strength also gradually decreases as the water reducing agent content gradually changes from 0% to 0.6%. The splitting tensile strength of HyFRAC with the water reducing agent content at 0% is 4.84% higher than that of the water reducing agent content at 0.6%. Obviously, the compressive strength and splitting tensile strength of HyFRAC decrease gradually with the increase of the water reducing agent content. The reason may be that the water reducing agent can generate a large number of tiny bubbles inside of HyFRAC (Hongxia, Zhifu, and Chaoping, Li, and Jianjian 2011; Aijiu, Jing, and Qing 2009). CHEN Ai-jiu (Aijiu, Jing, and Qing 2009) pointed out that the compressive strength of RAC decreased significantly with the increase of water reducing agent. When the water reducing agent content was 0.2%, 0.4% and 0.6%, the compressive strength of RAC decreased by 2.3%, 15.5% and 21.1%, respectively. These bubbles will cause the pore changes of HyFRAC, resulting in a decrease in compressive strength and splitting tensile strength.

### 3.4. Range analysis

The results of Table 5 were processed to obtain the range analysis results shown in Table 7. The factors influencing the compressive strength and splitting tensile strength of HyFRAC in sequence are the RBA/RCA ratio (Factor A), the water reducing agent content (Factor C) and the GF/PF ratio (Factor B). According to compressive strength of HyFRAC, for factor A (k4> k3> k1> k2), A4 was the optimum, while for factors B (k4> k3> k2> k1) and C (k1> k2> k3> k4), B4 and C1 were the optimum.

According to splitting tensile strength of HyFRAC, for factor A (k4> k3> k1> k2), A4 was the optimum, while as for factors B (k2> k1> k4> k3) and C (k1> k2> k4> k3), B2 and C1 were the optimum. Hence, the best scheme for compressive strength of HyFRAC is A4B4C1, and the best scheme for splitting tensile strength of HyFRAC is A4B4C1. It also can be found that the RBA/RCA ratio has the most significant effect on its strength, followed by the water reducing agent content, and finally the GF/PF ratio.

### 3.5. Variance analysis

The results of variance analysis are shown in Table 8. According to F value, the RBA/RCA ratio has the greatest influence on both compressive strength and splitting tensile strength, followed by the water reducing...
Table 8. Variance analysis table.

| Survey index | Source of variance | Sum of square | Degrees of freedom | Mean square | F   |
|--------------|--------------------|---------------|--------------------|-------------|-----|
| 28d compressive strength/MPa | Factor A | 191.28 | 3 | 63.76 | 21.96 |
|                | Factor B | 9.87   | 3 | 3.29  | 1.13  |
|                | Factor C | 30.91  | 3 | 10.30 | 3.55  |
|                | Error e  | 17.42  | 6 | 2.90  |       |
|                | Sum      | 249.49 | 15 |       |       |
| 28d splitting strength/MPa  | Factor A | 1.07   | 3 | 0.36  | 7.65  |
|                        | Factor B | 0.04   | 3 | 0.01  | 0.30  |
|                        | Factor C | 0.21   | 3 | 0.07  | 1.50  |
|                        | Error e  | 0.28   | 6 | 0.05  |       |
|                        | Sum      | 1.61   | 15 |       |       |

The agent content, and finally the GF/PF ratio, which is also almost consistent with the range analysis.

4. Prediction of compressive strength based on CNN

4.1. CNN theory

CNN is a kind of deep-learning neural network which has been developed in recent years. Data features are learned layer by layer through multiple convolution layers and pooling layers, which avoids the disadvantage of manual extraction of data features in traditional machine learning. Back propagation algorithm of CNN learning process is adopted, that is, adjusting the weight matrix by reducing the mean square error of ideal output and actual output. Finally, the invariant features of translation, rotation and scaling in the input data are obtained.

The data is input to the hidden layer through kernel function. The hidden layer is mainly composed of alternating convolution layer and pooling layer, as shown in Figure 9. Each feature matrix can be regarded as a plane. Different planes correspond to different convolution kernels, which makes feature extraction more sufficient. The calculation process of convolution is shown in Figure 10(a), and the calculation process of pooling is shown in Figure 10(b).

From the orthogonal test results, it can be seen that the RBA/RCA ratio, the GF/PF ratio and the water reducing agent content all have an effect on the strength of HyFRAC, and each factor is nonlinear with compressive strength. It is impossible to consider all factors in the test. However, the CNN based on the TensorFlow platform can build a neural network model based on the existing data and predict the unknown data, which provides a new method for the strength prediction of HyFRAC.

The steps of CNN are as follows:

1. inputting training data;
2. processing of input data by convolution kernel and bias;
3. non-linear mapping of the output result of convolution layer by the pooling effect of activation function;
4. The loss function converges and the error is fed back to the input layer until the loss function stabilizes by training of the optimizer;
5. outputting target data.

Calculation formula of convolution and pooling is shown in Equation (1):

\[ Y^m = f(\sum X^{s-1} \times W^m + B^m) \]  (1)

Where: \( Y \) is the convolution output; \( s \) is the number of convolution layers; \( X \) is the convolution input; \( f \) is the activation function; \( m \) is the convolution output dimension; \( W \) is the convolution kernel; \( B \) is the bias.

4.2. CNN model establishment

In this paper, columns ① and ② of the 28d compressive strength in Table 5 were used as training samples, and column ③ were used as the prediction samples to train and predict. The RBA/RCA
ratio, the GF/PF ratio and the water reducing agent content were used as convolution input, and the compressive strength was used as convolution output. The initial bias of CNN was set to zero, and the initial values of the convolution kernel and the bias were randomly generated. The activation function was Sigmoid, the loss function was Mean Squared Error, the optimizer was Gradient Descent Optimizer, the learning efficiency was 0.1, and the number of learning steps were 200,000. The CNN prediction model structure is shown in Figure 11.

### 4.3. Prediction results and analysis

The prediction values and relative errors of CNN model for training samples and prediction samples are shown

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**Figure 10.** Schematic diagram of convolution and pooling process (a) Convolution process (b) Pooling process.

**Figure 11.** CNN prediction model structure.
Table 9. CNN model prediction results.

| Specimen number | Compressive strength | Prediction samples |
|-----------------|----------------------|--------------------|
|                 | Training samples     | Prediction samples |
|                 | @Test value | @Predictive value | @Relative error | @Test value | @Predictive value | @Relative error | @Test value | @Predictive value | @Relative error |
| H-1             | 34.06        | 33.9437            | 0.34%           | 29.95      | 29.9609            | 0.04%           | 32.38      | 31.9468            | 1.34%           |
| H-2             | 34.51        | 34.6935            | 0.53%           | 32.74      | 32.7658            | 0.08%           | 33.62      | 33.7294            | 0.33%           |
| H-3             | 32.21        | 32.0399            | 0.53%           | 34.74      | 35.3368            | 1.72%           | 32.28      | 33.6110            | 4.12%           |
| H-4             | 31.91        | 31.7152            | 0.61%           | 31.92      | 32.1657            | 0.77%           | 33.84      | 32.6312            | 3.57%           |
| H-5             | 32.01        | 31.6966            | 0.98%           | 32.09      | 32.5059            | 1.30%           | 30.51      | 31.5364            | 3.36%           |
| H-6             | 32.28        | 32.2336            | 0.01%           | 34.19      | 34.3336            | 0.42%           | 33.21      | 33.0078            | 0.01%           |
| H-7             | 32.33        | 32.4848            | 0.48%           | 29.12      | 28.9794            | 0.48%           | 29.63      | 30.4427            | 2.74%           |
| H-8             | 31.39        | 31.4975            | 0.34%           | 32.53      | 32.5223            | 0.02%           | 29.25      | 29.7576            | 1.74%           |
| H-9             | 36.80        | 36.7374            | 0.17%           | 35.71      | 35.7501            | 0.11%           | 36.58      | 36.3582            | 0.61%           |
| H-10            | 29.95        | 29.8675            | 0.28%           | 34.13      | 34.3246            | 0.57%           | 31.20      | 32.2050            | 3.22%           |
| H-11            | 35.27        | 35.0206            | 0.71%           | 34.14      | 34.0829            | 0.17%           | 36.15      | 36.3033            | 0.43%           |
| H-12            | 36.60        | 36.8372            | 0.65%           | 36.76      | 36.4964            | 0.72%           | 36.53      | 36.2416            | 0.79%           |
| H-13            | 37.61        | 37.7896            | 0.48%           | 34.70      | 34.5313            | 0.49%           | 36.49      | 35.9319            | 1.53%           |
| H-14            | 39.45        | 39.6325            | 0.46%           | 40.96      | 40.5043            | 1.11%           | 37.50      | 39.0368            | 4.10%           |
| H-15            | 42.15        | 42.0094            | 0.33%           | 42.40      | 42.4439            | 0.10%           | 43.54      | 42.9210            | 1.42%           |
| H-16            | 44.54        | 44.6990            | 0.36%           | 45.39      | 45.3397            | 0.11%           | 42.78      | 43.8004            | 2.39%           |

Figure 12. Correlation between the predicted values of three models and the test values (a) CNN model (b) BP neural network model (c) Multiple linear regression model.
Table 10. The relative error of the prediction results of the three models.

| Model                  | Training samples | Prediction samples |
|------------------------|------------------|--------------------|
|                        | Average relative error/\% | Max relative error/\% | Average relative error/\% | Max relative error/\% |
| CNN                    | 0.48             | 1.72               | 1.98                | 4.12                |
| BP neural network      | 4.01             | 12.60              | 4.15                | 11.13               |
| Multiple linear regression | 5.79            | 11.48              | 5.76                | 13.72               |

in Table 9. It can be seen that the average relative errors and max relative errors of the compressive strength for training samples are 0.48% and 1.72%, respectively. The average relative errors and max relative error of the compressive strength for prediction samples are 1.98% and 4.12%, respectively. All statistical values prove that the values obtained through the training and prediction of CNN model are very close to test results.

In order to compare the prediction accuracy of CNN model, based on the above data, BP neural network model and multiple linear regression model were also used for prediction. As shown in the Figure 12, the coefficient of determination for the CNN model is determined as $R^2 = 0.9637$. In addition, the BP neural network model and multiple linear regression model are determined as $R^2 = 0.8098$ and $R^2 = 0.7064$, respectively. As it is illustrated in Table 10 that the average relative errors and max relative errors of the CNN model are 1.98% and 4.12%, respectively; the average relative errors and max relative errors of the BP neural network model are 4.15% and 11.13%, respectively; and the average relative errors and max relative errors of the multiple linear regression model are 5.76% and 13.72%, respectively. Figure 13 shows that the relative errors of CNN model are less than 5%, and the probability distribution range is most concentrated, while the max relative errors of BP neural network model and multiple linear regression model are more than 10%, and the probability distribution range is scattered. To conclude, the CNN model is efficient in estimating the compressive strength of HyFRAC, as compared to the BP neural network model and multiple linear regression model. In the research of Fangming Deng (Deng et al. 2018), the maximum and minimum relative errors of CNN model are 18.93% and 0.01%, respectively, which has higher prediction accuracy than BP neural network. GAO Wei (2018) also found that the maximum absolute error of CNN model in predicting concrete compressive strength was 0.5 MPa. The above research shows that CNN model has higher prediction accuracy and stronger generalization ability.

5. Conclusions

In this paper, the orthogonal test design method was used to analyze the effects of the RBA/RCA ratio, the GF/PF ratio, and the water reducing agent content on the strength of HyFRAC. In addition, CNN has been used to predict the test results. The following conclusions were summarized as follows:

1) The compressive strength and splitting tensile strength of RAC were improved by Hybrid fiber. The compressive strength of HyFRAC ($A_dB_4C_1$) is 1.34 times and 1.64 times of RCAC and RBAC, respectively. The splitting tensile strength of HyFRAC ($A_dB_4C_1$) is 1.64 times and 1.93 times of RCAC and RBAC, respectively.

2) The slump of HyFRAC increases gradually as the water reducing agent content gradually changes from 0% to 0.6%. According to JG/T10-2011, when RBA/RCA ≤ 6/4 and water reducing agent content ≥ 0.4%, the HyFRAC slump meets the requirement of 50 m pumping height; when RBA/RCA ≤ 4/6 and water reducing agent content ≥ 0.6%, the HyFRAC

![Figure 13. Probability distribution of relative error (a)Probability distribution (b)Cumulative probability distribution.](image-url)
slump meets the requirement of 100 m pumping height.

3) The RBA/RCA ratio has been proved the greatest influence on the compressive strength and splitting tensile strength of HyFRAC, followed by the content of water reducing agent, finally the GF/PF ratio. The compressive strength and splitting tensile strength increase as the RBA/RCA ratio decreases, and decrease as the water reducing agent content increases. The influence of the GF/PF ratio on compressive strength and splitting tensile strength is different. As the GF/PF ratio increases, the compressive strength increases, while the GF/PF ratio has little effect on the splitting tensile strength. when the RBA/RCA ratio is 2/8, the GF/PF ratio is 7/3, and the water reducing agent content is 0%, the compressive strength and splitting tensile strength of HyFRAC are the highest. The best scheme for compressive strength of HyFRAC is A1B2C1, and the best scheme for splitting tensile strength of HyFRAC is A4B2C1.

4) When the RBA/RCA ratio gradually changes from 8/2 to 2/8, the compressive strength gradually increases. The compressive strength of HyFRAC with RBA/RCA = 2/8 increased by 23.56% compared to the specimen with RBA/RCA = 8/2. The splitting tensile strength of concrete should increase with the decrease of the RBA/RCA ratio. The splitting tensile strength of HyFRAC with RBA/RCA = 8/2 increased by 14.87% compared to the specimen with RBA/RCA = 6/4.

5) The compressive strength gradually increases as the GF/PF ratio gradually changes from 1/9 to 7/3. The compressive strength of HyFRAC with GF/PF = 7/3 increased by 6.01% compared to the compressive strength of HyFRAC with GF/PF = 1/9. The influence of the GF/PF ratio from 1/9 to 7/3 on the splitting tensile strength is not obvious. The compressive strength of HyFRAC with GF/PF = 3/7 is only 2.86% higher than the compressive strength of GF/PF = 5/5.

6) The compressive strength gradually decreases as the water reducing agent content gradually changes from 0% to 0.6%. The compressive strength of HyFRAC with the water reducing agent content at 0% is 10.56% higher than that of the water reducing agent content at 0.6%. The splitting tensile strength also gradually decreases as the water reducing agent content gradually changes from 0% to 0.6%. The splitting tensile strength of HyFRAC with the water reducing agent content at 0% is 4.84% higher than that of the water reducing agent content at 0.6%.

7) The CNN model is efficient in estimating the compressive strength of HyFRAC, as compared to the BP neural network model and multiple linear regression model. The average relative errors and max relative errors of the CNN model are 1.98% and 4.12%, respectively; the average relative errors and max relative errors of the BP neural network model are 4.15% and 11.13%, respectively; and the average relative errors and max relative errors of the multiple linear regression model are 5.76% and 13.72%, respectively.

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