Chapter 6
Discussion on the Establishment and Application of Intelligent Design Platform for Concrete Proportioning

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Abstract More than 3 billion m^3 of ready-mixed concrete was produced nationally in 2021, the largest structural engineering materials for transportation and urban construction. The key to ensuring project quality and cost optimization is the design of the concrete mix ratio. The system shares the massive concrete raw material, mix ratio, compressive strength, and real-time testing data deposited by concrete producers to the cloud (Ali cloud) through the concrete mix ratio intelligent design and sharing platform. It provides real-time feedback to guide the adjustment and optimization of the mix ratio through the machine learning algorithm deployed in the cloud, integrating expert knowledge, deep neural network, and Monte Carlo algorithm. It also carries out 28-day concrete compressive strength prediction. The platform and terminal equipment realize the digitization and sharing of data related to concrete ratio design, which is an important carrier for the industrialization of concrete mix data and is of great significance to cost reduction and efficiency of engineering construction, as well as having great potential commercial value. For the application scenario of slab ballastless track, a test device for intelligent testing of key properties of self-compacting concrete (SCC) is designed and produced, relying on the intelligent design and sharing platform to realize the collection, storage, analysis, and application of SCC data.

6.1 Introduction

Machine learning is capable of mining laws and knowledge from complex data through various computational models and algorithms. It has become one of the core technologies in contemporary artificial intelligence. Deep neural networks, with the

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advantage of fitting nonlinear problems, have been used to predict the key properties of concrete and mix ratio design [1]. It has been shown that the use of deep learning techniques for concrete proportion design is an effective way to address the design of concrete proportions for complex components.

Ren et al. introduced a new approach to optimize the proportion design of high-performance concrete (HPC) for multiple objectives, including compressive strength, production cost, and carbon emissions, using artificial intelligence algorithms and metaheuristic search techniques [2]. The effectiveness and superiority of this method have been successfully demonstrated through its application in a specific engineering project [3]. Zhao discussed potential issues that may arise when integrating the concrete industry with the artificial intelligence industry. It is important to note that effective communication between the concrete and artificial intelligence industries requires individuals with relevant knowledge to act as intermediaries, and the cultivation of such personnel is necessary [4]. For the two core requirements of intelligent concrete mix design and accurate prediction of concrete properties, four technical aspects are described in this paper. Firstly, hardware, basic network construction, computer hardware, and equipment intelligent transformation are carried out; then data collection system deployment and development are carried out; then the intelligent design and sharing platform of the mix ratio is established; finally, big data mining and analysis of the platform are carried out and developed and applied.

Based on the intelligent design and sharing platform of concrete ratio, a special concrete performance testing device is designed for the rheological properties, construction performance, and forming quality of CRTSIII SCC application scenarios, which builds a physical platform for data collection of the same type of concrete and establishes a data foundation for intelligent design of this type of concrete.

6.2 Platform Architecture

A necessary prerequisite for intelligent concrete mix design is the acquisition, processing, and application of raw material, mix, and performance data obtained from existing concrete business operations. In pursuit of this objective, a series of technological advancements have been pursued to optimize data utilization and enhance the intelligence of concrete mix design. As shown in Fig. 6.1, we virtualized the data in the host, storage, network, and other infrastructure to form a pool of resources such as computing resources, storage resources, and network resources. This allows us to flexibly adjust the resource allocation to meet the needs of different application scenarios.

In the specific implementation process, we relied on Chongqing Construction Industry Building Materials Logistics Co., Ltd. to establish a database covering raw materials, mixing ratios, and performance data. This database includes various key data generated in the production process of the enterprise, such as cement type, aggregate grade, admixture content, etc. By analyzing these data in detail, we can

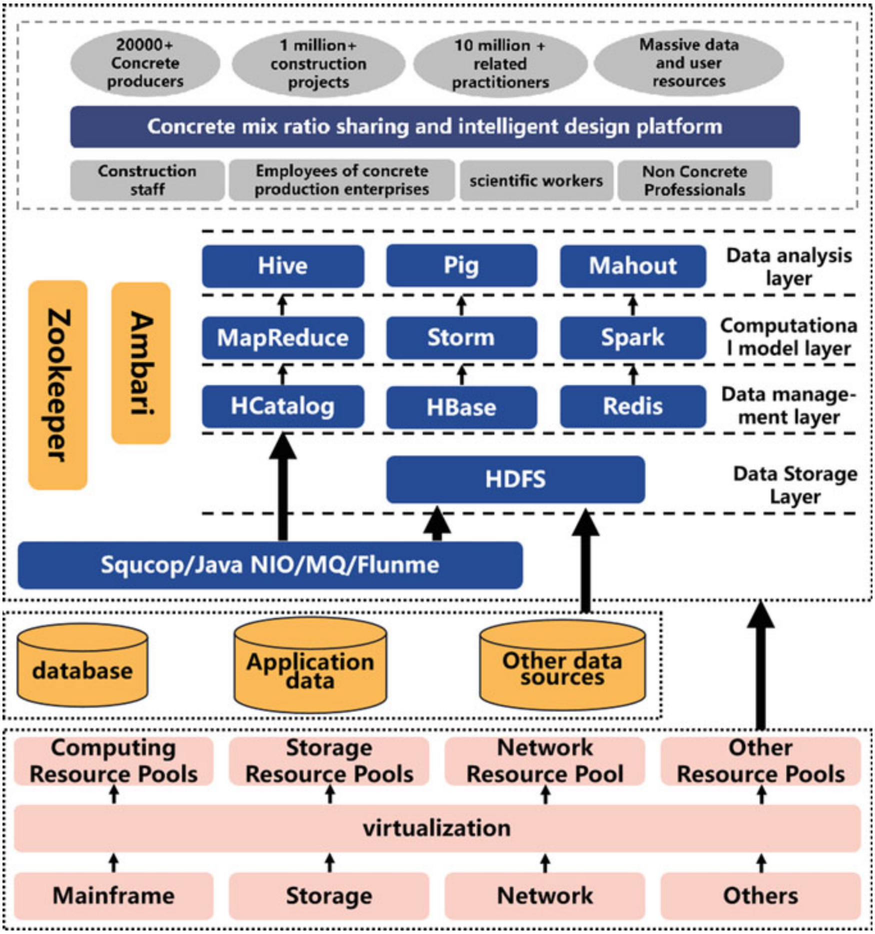


Fig. 6.1 Overall architecture of the intelligent design and sharing platform for concrete mix ratio

gain a more comprehensive understanding of the various variables in the concrete production process and provide a basis for intelligent design.

To further enrich the database, we also intend to use other infrastructures to collect specific data for specific application scenarios. For example, special equipment was developed to measure and upload the performance of key indicators of self-compacting concrete (SCC) for ballastless track, and a special database was created. This data will not only help us to better understand the concrete performance requirements in these specific scenarios, but will also provide additional reference information for our intelligent design.

6.3 Design Scheme

The platform proposes a prediction model for 28-day compressive strength of concrete based on integrated learning, considering that the prediction ability of multiple models is stronger than that of a single model. Subsequently, considering that deep learning has a more mature framework and can adapt to the real-time required for production, by weighing the advantages of deep learning and integrated learning, a deep learning-based intelligent concrete mix ratio design model is proposed, which selects the mix ratio by establishing an expert knowledge base, adjusts the mix ratio with Monte Carlo random scoring, and uses a deep learning-based concrete performance prediction method. Finally, the cost of concrete mix ratio is used as the optimization target to find the optimal value.

6.3.1 Record Extraction and Cost Optimization

On the application terminal, the user enters the technical requirements of the desired target concrete and the varieties of raw materials and their performance indexes through the intelligent design page, and then searches, matches, and scores a large number of records in the cloud concrete database through the matching rule table summarized from the expert experience, and the 10 records with the highest scores are used as the results of the initial screening and transmitted in the form of an alternative set to the intelligent design model. Then, based on the records matched by the database, the intelligent design model integrates expert knowledge, deep neural network, and raw material prices, and uses Monte Carlo search algorithm to find a set of optimal mix ratio design solutions in the domain knowledge space. Finally, this solution and the 10 historical records matched by the database are put back to the intelligent design page as the final result [5, 6].

The ultimate goal of the intelligent design is to minimize the unit cost of the concrete while satisfying the target concrete performance requirements and proportional constraints. According to this objective, the mathematical expression of optimal cost model is shown in Fig. 6.2. After determining the optimization target, the concrete mix fine-tuning specific steps are shown in Fig. 6.2: the user needs to filter out the concrete production mix with the highest rating in the database as the benchmark mix through the scoring rules, calculate the production cost of the mix as the preset optimal mix unit production cost Cost_min, set d to 0, set the maximum effective number of counts $d_{\max}$ to 50,000 times, carry out Iterative calculation, and finally achieve the purpose of cost reduction. "d" refers to the number of iterations of the process.

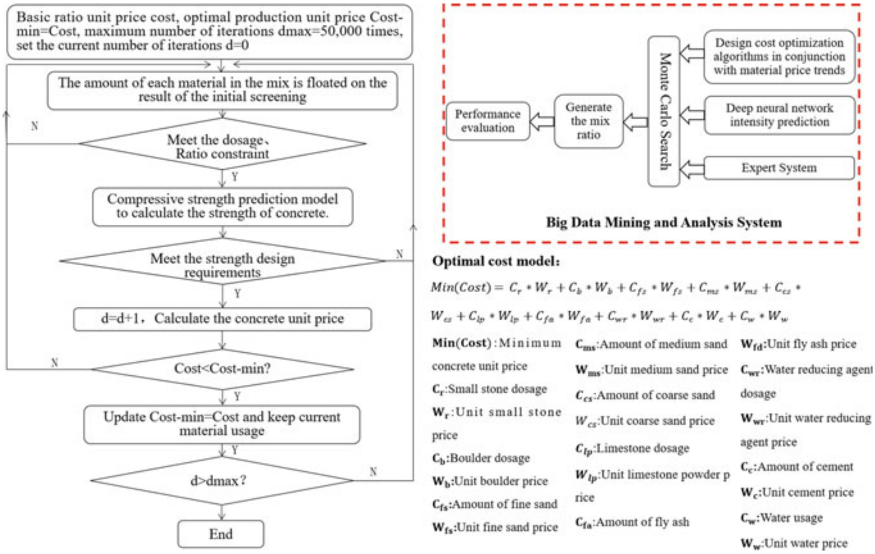


Fig. 6.2 Cost optimization model

6.3.2 Compressive Strength Prediction Model

The prediction model framework for the 28-day compressive strength of concrete is shown in Fig. 6.3. The model mainly consists of four components: data preprocessing, feature engineering, ADARF (AdaBoost Method Based on Random Forests) regression model, and performance evaluation criteria. Because of manual data collection, data entry, and other factors, the provided concrete data have problems with missing data and noise. Therefore, we need to perform data preprocessing on historical data, which mainly includes eliminating outliers, removing duplicate data, and missing value filling. After data preprocessing, this paper analyzes the heat map, consults industry experts for feature selection and fusion, and finally selects common regression evaluation indexes to evaluate the performance of the model, as shown in Fig. 6.3.

The concrete mix production dataset provided by Chongqing Construction Group contains 11 attributes, covering 9,500 production data from January to December 2018. Of these, 3 attributes are related to concrete mix production, while 28 attributes are related to concrete production conditions and performance testing. The dataset has been preprocessed and cleaned, including removing missing values, deleting duplicate data, removing outliers, and filling in missing values. Pearson correlation coefficients and consultations with concrete experts were used for feature selection and combination. For the first type of attribute, missing values were replaced with 0 to indicate that the material was not used. For the second type of attribute, missing values were filled in with the median value to obtain the best predictive performance. The second type of attribute related to concrete production conditions was encoded

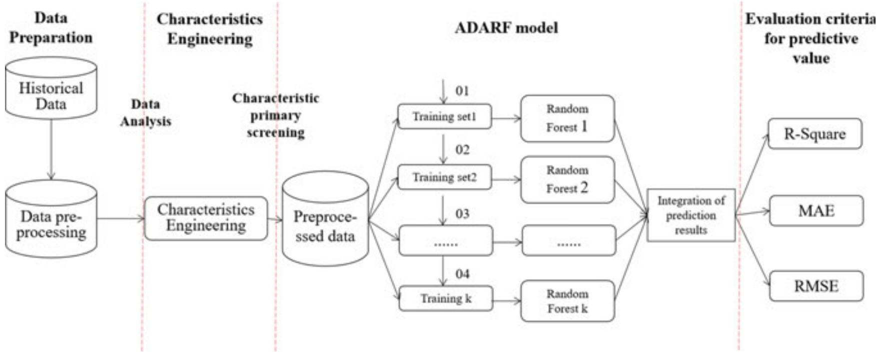


Fig. 6.3 Prediction model for 28-day compressive strength of concrete

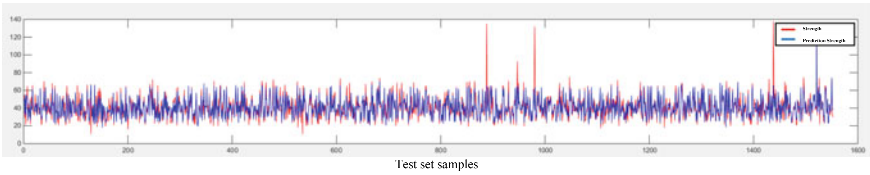


Fig. 6.4 Actual compressive strength versus model-predicted compressive strength

using ordered numbers for better performance. Overall, the dataset contains rich information, and after preprocessing and feature selection, it can be used to establish a concrete compressive strength prediction model [7].

The actual compressive strength of concrete on the test set at the same time and the model-predicted compressive strength are shown in Fig. 6.4, with red representing the actual compressive strength and blue representing the predicted compressive strength. As can be seen from the figure, the neural network operation results match well with the actual compressive strength and their regression values with good accuracy. Only three groups of ultra high compressive strength concrete predicted values can be seen as significant errors, because they exceed the predicted threshold. The online capability of the built BP neural network is strong through experimental testing, which can adapt to the high real-time requirement of the concrete intelligent proportioning design model.

6.3.3 Performance Testing Device of CRTSIII SCC

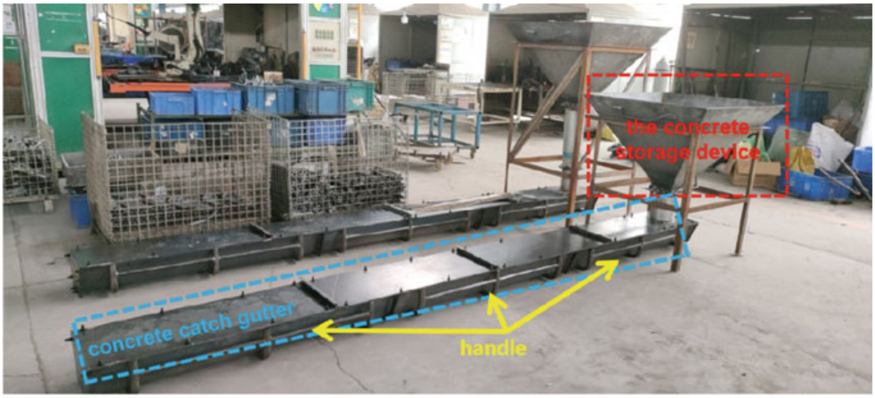
CRTSIII SCC is a type of concrete with high fluidity, resistance to segregation, and gap passage properties. Before construction, the SCC must be subjected to a process test—the uncovering test. The uncovering test is mainly to observe the working performance of concrete during the filling process, to uncover the slab 24 h after filling, and to judge the forming quality of SCC by inspecting the air bubbles on the joint surface and section of concrete. The ratio will then be empirically adjusted in conjunction with the ambient temperature and humidity conditions. This test is tedious, time-consuming, and labor-intensive, and the empirical judgment by visual inspection is less efficient and accurate. It cannot form a systematic method for adjusting the mix ratio. The uncovering test has specific requirements for the site, which cannot be met by ordinary R&D laboratories. At the same time, concrete is highly sensitive to materials and environment, and a small change in the mix ratio will have a large impact on the concrete performance. Therefore, we have designed a device that can standardize the performance testing of the same type of SCC, taking into account the actual needs. The device is small enough to be used in the scenarios of laboratory and mixing plant, and can be used to standardize the recording, performance data, and conditions, then store them. The application of this device is an attempt to the concrete intelligent design platform in the design of special concrete mixes.

In order to meet the special performance inspection requirements of CRTSIII SCC [8], our design scheme is as follows: the test storage device is an inverted quadrilateral cone-shaped feeding cylinder that can control the concrete filling volume and characterize the concrete viscosity by detecting the concrete outflow time; the length of the device chute is set to 4.2 m according to the distance from the track slab to the filling port in engineering applications, and the discharge port is designed For observation; In order to release the concrete after hardening, the concrete chute cross-section is designed as inverted trapezoid, and handrails are set around;In order to clearly observe the concrete flow state, the chute cover is designed as acrylic transparent material, and at the same time, a sheet pressure detection module is installed on the chute cover to measure the jacking force after the concrete filling is completed;Spacers were set at four equal parts of the chute to simulate distribution of reinforcement, with the aim of testing its gap passage performance. The model drawing is shown in Fig. 6.5.

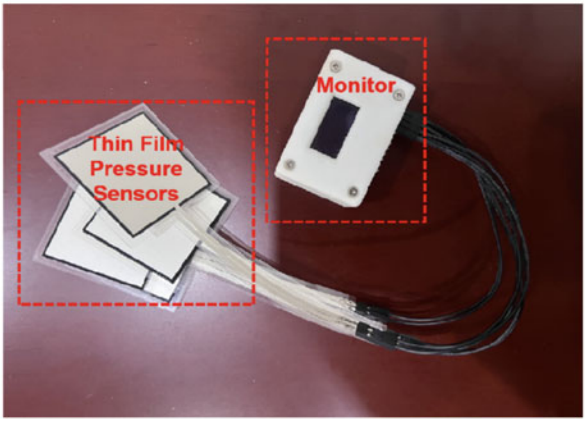
6.4 Technical Architecture and Application

The system forms a complete technical architecture by establishing an intelligent design and sharing platform for concrete, designing an intelligent design scheme for the mix ratio, constructing a pre-integrated prediction model for the 28-day compressive strength of concrete, and inventing an intelligent data collection terminal such as performance testing device of CRTSIII SCC, which can realize data collection in various ways, mix ratio design for various needs, data extraction, optimization and prediction.

The system has a wide range of application scenarios. For professional concrete production enterprises, the production process requires a large number of concrete ratio design work. There is a large amount of raw materials, ratio, and performance data, which can supplement and improve the database. For non-professional units



(a)Performance testing device of CRTS□ SCC



(b)Acrylic cover plate (c)Pressure detection device

Fig. 6.5 Performance Testing Device for CRTSIII SCC

and on-site mixing stations, it can lower the threshold of the industry and improve the efficiency and accuracy of the mix design. For universities and research institutions, it provides new ways for data collection and analysis. For special concrete projects, it provides a data interface for concrete with special performance requirements, and realizes data collection, storage, analysis, and application. The technical architecture and application are shown in Fig. 6.6.

Based on this, relevant tests were conducted in this study. Firstly, the target mix design parameters were determined as follows: compressive strength grade C30, variety: ordinary concrete, slump: 200 mm, expansion: 500 mm, impermeability grade: P6. The source material information was as follows: cement from Chongqing Xiaonanhai Cement Plant, variety grade: P·O42.5R; fine aggregate 1: fine sand, fine

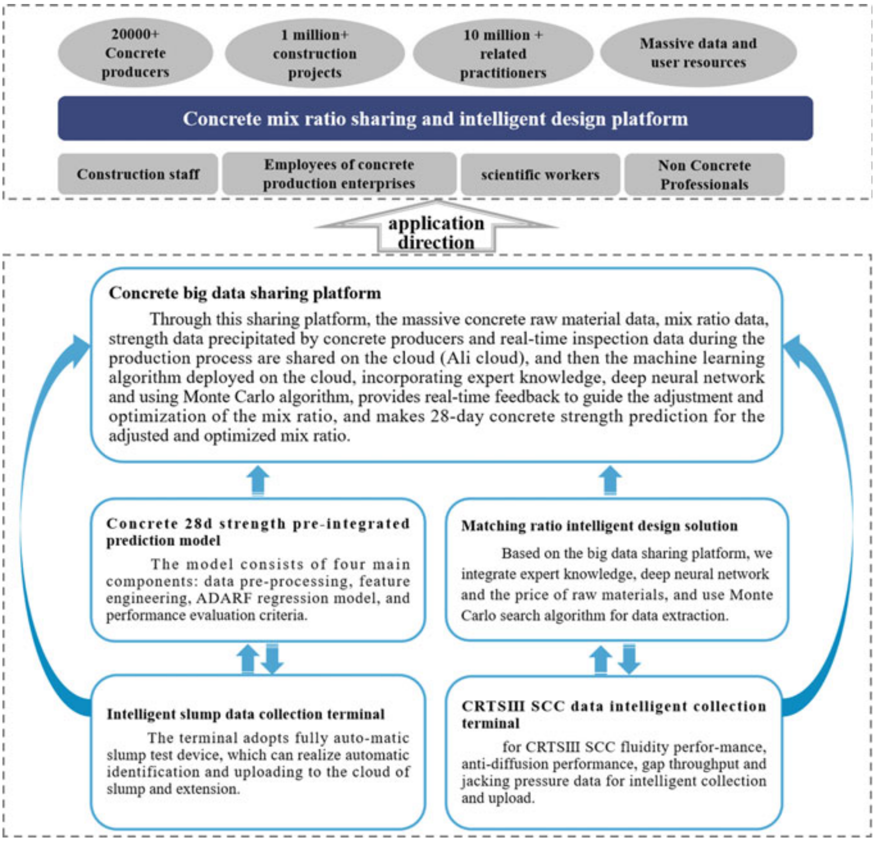


Fig. 6.6 Technical architecture and application direction

aggregate 2: medium sand; coarse aggregate 1: 5–10 mm, coarse aggregate 2: 10–20 mm; water reducing agent variety: PCA-l polycarboxylic acid high-performance water reducing agent; water reducing rate: 30%.

Finally, the target concrete mix design was developed, with the dosage per cubic meter (kg) of cement, coarse aggregate 1, coarse aggregate 2, fine aggregate 1, fine aggregate 2, water, and water reducing agent being 315, 375, 709, 12, 804, 160, and 6.53, respectively. The calculated density of the concrete was 2382 kg/m^3, and the compressive strength prediction model yielded a compressive strength of 45.3 MPa at 28 days, which met the design requirements.

6.5 Conclusion

Concrete mix ratio intelligent design and sharing platform is the product of the combination of traditional concrete producers and digital technology, which has significantly improved the accuracy and efficiency of concrete mix ratio design and saved engineering costs. The platform has been developed into a SaaS product and is now open to a wider range of construction workers, concrete producers, scientists, and non-concrete professionals, greatly improving the intelligence of concrete mix design, improving the efficiency and accuracy of design, lowering the technical threshold of relevant practitioners, and providing a new solution to problems related to the design of special concrete mixes.

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