# Intelligent Prediction of Dynamic Yield Stress in 3D Printing Concrete Based on Machine Learning

Songyuan Geng [1, a], Wujian Long [1, b], Qiling Luo [1, c], Junen Fu [3, d], Wenya Yang [4, e], Huanzhou He [5, f], Qiubing Ren [6, g], and Chuanglian Luo [2, *]

[1] College of Civil and Transportation Engineering, Shenzhen University, Shenzhen 518060, Guangdong, China;

[2] Guangzhou Guangjian Construction Engineering Testing Center Co., Ltd., Guangzhou 510405, Guangdong, China;

[3] China Railway Construction Bridge Engineering Bureau group Co., Ltd., 300300, Tianjin, China;

[4] Poly Changda Engineering Co., Ltd., Guangzhou 510640, Guangdong, China;

[5] Shenzhen Yantiangang Construction Engineering Test Co., Ltd., Shenzhen 518081, Guangdong, China;

[6] Tianjin University, 300354, Tianjin, China.

[a] gengsongyuan2022@email.szu.edu.cn, [b] longwj@szu.edu.cn, [c] Luoqiling@szu.edu.cn, [d] 251580278@qq.com, [e] seuywy@163.com, [f] hhz@ytgtest.com, [g] qbren@tju.edu.cn

* Corresponding author at: No.5, Lane 3, Siyou North 1st Street, Guangzhou, Guangdong, China

E-mail address: Luo_lian@126.com

**Abstract.** Applying 3D printing technology to the construction industry can bring many benefits. However, due to the specificity of 3D printing technology, its application in the construction industry has not yet been promoted. Machine learning (ML) techniques, which are popular at this stage, are expected to provide solutions to these problems. Rheological properties have been a key parameter for the quality of 3D printing concrete, and its accurate prediction can help to integrate 3D printing technology into the construction industry. In this study, a GA-RF model for predicting the dynamic yield stress (DYS) of 3D printing concrete is proposed for the first time, and the hyperparameters of the RF model are intelligently tuned during the training process. In addition, the importance analysis of the input parameters is performed. The results show that the developed prediction model has a high accuracy and the SF content has the most significant effect on DYS. The research results help to advance the construction industry to mass production of 3D printing concrete.

**Keywords:** Machine Learning; 3D printing; dynamic yield stress; intelligent prediction.

## 1. Introduction

3D printing concrete refers to the use of CNC machines or similar equipment to print concrete materials in layers as required in design drawings to form complex concrete structures. The concept of 3D printing concrete can be traced back to the 1980s, when scientists began to explore the use of machines to automate the production of concrete structures [1]. The concept of 3D printing concrete was first introduced in the 1980s. In the 2000s, the concrete industry began experimenting with 3D printing technology. In the 2010s, 3D printing concrete technology began to mature and its applications expanded to include buildings, bridges, roads, etc. In 2014, Chinese construction materials company Winsun successfully printed 10 concrete structures, including a five-story home. In the 2020s, 3D printing concrete technology is gaining popularity and adoption. For example, European construction company PERI has developed a mobile 3D printer that can print concrete on site for building curved-shaped structures [2]. Compared to traditional construction methods, 3D printing concrete has the following advantages: 1) Saves time and labor costs: While traditional construction methods require a lot of labor and time, 3D printing concrete can print buildings in a shorter period of time, thus reducing labor and time costs. 2) Can print complex shapes: 3D printing concrete can print complex structures and shapes, allowing for richer and more diverse architectural designs. 3) Reduced waste and environmental protection: 3D printing concrete can be tailored to the amount of material needed, thus reducing waste. In addition, this technology allows the use of renewable materials, thus reducing the environmental impact. 4) It can reduce safety risks at the building construction site: 3D printing concrete can reduce the risk of workers operating and working at the building site, thus improving the safety of construction [3]. Although the development of 3D printing concrete technology is still in its early stages, it will play an important role in the construction and engineering field as the technology continues to advance and its applications expand [4].

However, 3D printing concrete technology still has some limitations [5]. First, 3D printing concrete technology is not yet fully mature, so there are still technical problems and defects in the production process. For example, cracks and defects may occur during the printing process, thus affecting the strength and durability of the building. In addition, the construction process needs to control the ambient temperature and humidity to ensure the quality and performance of the concrete. Second, the application of 3D printing concrete technology is still relatively limited. Currently, this technology is mainly applied to the manufacturing of building components, such as walls and columns. For large structures, such as bridges and high-rise buildings, further exploration and research are needed. In addition, 3D printing concrete technology cannot yet completely replace traditional construction methods, which can still be applied to certain situations and specific needs. In addition, there are some material and cost issues with 3D printing concrete technology. Currently, the materials required for 3D printing concrete are still relatively expensive and in some cases may not be environmentally friendly enough. In addition, this technology requires specialized equipment and operating techniques, which adds to the cost and technical difficulty.

As technology continues to evolve, artificial intelligence (AI) has also become popular in people's lives [6]. AI is a technology and theory in the field of computer science that involves the simulation, replication and extension of the implementation of human intelligence. In simple terms, AI is the ability to enable computers to think, learn, understand and perform tasks as humans do. The concept of artificial intelligence can be divided into strong AI and weak AI. Strong AI is an intelligent system that can perform all tasks at the human intelligence level, while weak AI is an intelligent system that can only perform specific tasks. AI technologies mainly include ML, deep learning, natural language processing, computer vision, speech recognition, knowledge mapping, intelligent recommendation, and so on [7]. These technologies can help computer systems understand and process large amounts of data and generate models and algorithms based on the data so that they can learn and improve on their own. ML is a branch of artificial intelligence that uses algorithms and mathematical models to enable computer systems to learn and improve from data automatically, without explicitly programming instructions. In the field of AI, ML is a core technology that helps computer systems simulate intelligent human behavior to enable intelligent applications and solve real-world problems [8].

ML has many applications in the construction industry [9], and its main advantages include: 1) More efficient design and construction: ML can help architects and engineers analyze and optimize building designs to complete construction more quickly and accurately. For example, the mechanical behavior of building structures can be simulated using ML techniques to predict and solve potential structural problems in advance, reducing construction time and costs. 2) Cost savings: ML can help construction companies predict data on material costs, labor costs, construction time, etc. to get a better handle on costs and resources and avoid over-budget and delay problems. 3) Improved safety: ML can help construction companies and workers better manage and monitor site safety, predict and prevent potential hazards and accidents, and reduce safety risks. 4) Accurate maintenance and management: Using ML technology, the performance of various equipment and systems in buildings can be monitored, and potential problems can be identified and solved in advance, resulting in more accurate maintenance and management. 5) Better sustainability: ML can help construction companies and engineers to design and plan more sustainable buildings, optimize energy use and reduce environmental impact. And for 3D printing concrete, ML can help optimize concrete recipes and printing parameters, resulting in higher quality 3D printing concrete structures [10]. By analyzing large amounts of data, ML can identify correlations between various materials and parameters, and make predictions and optimizations based on these correlations to achieve better printing results and material strength. Second, ML can help improve the reliability and stability of 3D printing concrete structures. Using ML technology, parameters such as temperature, flow rate, and pressure during 3D printing can be monitored in real time, and printing parameters can be adjusted based on real-time data to ensure print quality and structural stability. In addition, ML can help design more complex and innovative 3D printing concrete structures. By training ML models, a large number of design samples can be generated and the optimal design solution can be found through evaluation and optimization. This approach can greatly improve design efficiency and innovation, and enable more diverse and personalized 3D printing concrete structures. Finally, ML can help improve the sustainability of 3D printing concrete structures. By analyzing the impact of various materials and parameters, concrete recipes and printing parameters can be optimized, thus reducing the consumption of materials and energy and the environmental impact.

Based on these advantages, ML methods have been successfully used to predict various properties of concrete, such as compressive strength [11], flexural strength [12], and splitting tensile strength [13], etc. However, the research on predicting the rheological properties of 3D printing concrete using ML methods is still in a gap, which greatly hinders the promotion of 3D printing technology in practical engineering applications. To overcome the above problems, this study uses a random forest (RF) model to predict the DYS of 3D printing concrete, in which the hyperparameters of the RF model are also intelligently tuned by the genetic algorithm (GA). The results of this study can provide engineers with relevant theoretical references and experimental validation.

## 2. Methodology

### 2.1 Machine learning methods

2.1.1 Random forest

RF is an integrated learning method, which is a model consisting of multiple decision trees. Each decision tree is trained based on randomly selected features and samples [14]. In prediction, RF averages or votes the prediction results of each decision tree to get the final prediction result. The RF model can effectively handle high-dimensional data with good prediction performance, as well as identify interactions between features and handle missing values and outliers. In addition, it can also estimate the importance of features and help identify important features. RF models have a wide range of applications in many fields, such as classification, regression, and feature selection. In conclusion, the RF model is a very popular machine learning algorithm that has achieved good results in many practical applications.

2.1.2 Genetic algorithm

GA is an optimization algorithm based on the principles of natural selection and genetics, which can be used to solve complex optimization problems. GA is a heuristic search method that optimizes the solution of a problem step by step by simulating the biological evolution process in nature [15]. Its basic process is as follows:

- Initialization: generating a random initial population, where each individual represents a possible solution;
- Selection: using a fitness function to evaluate the fitness of each individual and selecting some individuals as parents based on their fitness;
- Crossover: a crossover operation is performed on the selected parents to generate new progeny individuals;

- Mutation: perform mutation operations on new progeny individuals to introduce new genetic changes;
- Evaluation: calculating the fitness of each individual and selecting some individuals as parents of the next generation;
- Termination condition: stops the iteration and returns the optimal solution when certain termination conditions are met.

GA is able to search in high-dimensional spaces and do not require the derivatives of the solution function. Due to the stochastic nature, the GA has a good global search capability and can avoid getting trapped in a local optimal solution. In addition, it can handle multiple objective functions and consider optimization problems with multiple objectives simultaneously. GA is a general optimization method that can be applied to different types of problems. GA have been widely used in many fields, such as function optimization, ML, image processing, etc.

### 2.2 Hyperparameters tuning

The RF model has many hyperparameters, such as the number of decision trees (Max_DT), the maximum depth of each decision tree (Max_depth), the minimum number of samples of nodes in each decision tree (Min_samples_split), the minimum number of samples at the leaf node (Min_samples_leaf), and The number of features considered during the selection of the best splitting (Max_features). The selection of these hyperparameters has a great impact on the performance and generalization ability of the model, but hyperparameter search is a complex process that requires trying many different combinations to find the optimal hyperparameters. This is where optimization algorithms can be used to optimize the hyperparameters of the RF model [16]. The GA can perform a global search for hyperparameters to find the optimal combination of hyperparameters, so it is chosen as the optimization algorithm to optimize the hyperparameters of the RF model. The specific process is as follows:

- Define the fitness function: the fitness function needs to be defined according to the performance indicators of the model, such as accuracy, precision, recall, etc;
- Initialize the population: generate a random initial population with each individual representing a combination of hyperparameters;
- Evaluating fitness: evaluating each individual and calculating its fitness;
- Selecting parents: selecting individuals based on fitness and selecting some outstanding individuals as parents of the next generation;
- Crossover operations: crossover operations are performed on the selected parents to generate new offspring individuals;
- Mutation operation: perform mutation operation on new progeny individuals to introduce new genetic changes;
- Assessing the fitness of new individuals: calculating the fitness of newly generated individuals;
- Selecting the next generation of sires: selecting the next generation of sires based on fitness;
- Termination condition: stop the iteration and return the optimal solution when certain termination conditions are satisfied.

### 2.3 Model evaluation

To evaluate the training and prediction effects of the random forest model, coefficient of determination ($R^2$), mean absolute error (*MAE*), and root mean square error (*RMSE*) metrics are used for the analysis in this study. They are calculated in Eq. (1)-(3).

$$R^2 = 1 - \frac{\sum_{j=1}^{m}\left(p_j - t_j\right)^2}{\sum_{j=1}^{m}\left(t_j - \bar{t}_j\right)^2} \tag{1}$$

$$MAE = \frac{\sum_{j=1}^{m}\left|t_j - p_j\right|}{n} \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{j=1}^{m}\left(t_j - p_j\right)^2}{n}} \tag{3}$$

In the equation, $t_j$ is the experimental value; $p_j$ is the predicted value; $\bar{t_j}$ is the target mean value; m is the total number of instances used in modeling.

## 3. Data description

In this study, a database is created based on experimental data from the literature [17-23], containing 300 data sets, whose descriptive statistics are presented in Table 1. The input parameters in the model are OPC, SAC, SF, FA, S, MAXSS, TA, ESA, SP/B, and W/B, and the output parameters are DYS. Fig. 1 shows the details of the pair matrices.

Table 1. Descriptive statistics of the model parameters used to predict DYS

| Descriptive statistic | Input parameters | | | | | | | | | | Output parameters |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | OPC | SAC | SF | FA | S | MAXSS | TA | ESA | SP/B | W/B | DYS |
| | (kg/m$^3$) | (kg/m$^3$) | (kg/m$^3$) | (kg/m$^3$) | (kg/m$^3$) | (mm) | (kg/m$^3$) | (kg/m$^3$) | / | / | (Pa) |
| Mean | 588.15 | 9.11 | 58.44 | 52.70 | 670.29 | 0.71 | 1.37 | 1.99 | 0.05 | 0.40 | 633.52 |
| Min | 390.00 | 0.00 | 0.00 | 0.00 | 424.59 | 0.50 | 0.00 | 0.00 | 0.00 | 0.33 | 11.00 |
| Max | 1000.00 | 110.00 | 295.08 | 200.00 | 1250.00 | 1.75 | 7.50 | 4.95 | 0.50 | 0.52 | 4940.00 |
| Sum | 59403.06 | 920.00 | 5902.72 | 5322.80 | 67699.39 | 71.90 | 138.80 | 201.30 | 5.31 | 40.51 | 63986.00 |
| C | 101.00 | 101.00 | 101.00 | 101.00 | 101.00 | 101.00 | 101.00 | 101.00 | 101.00 | 101.00 | 101.00 |

Note: OPC denotes ordinary portland cement content (kg/m$^3$); SAC denotes sulphate aluminate cement content (kg/m$^3$); SF denotes silica fume content (kg/m$^3$); FA denotes fly ash content (kg/m$^3$); S denotes sand content (kg/m$^3$); MAXSS denotes maximum sand particle size (mm); TA denotes thixotropic agent content (kg/m$^3$); ESA denotes early strength agent content (kg/m$^3$); SP/B denotes superplasticizer/binder (-); W/B denotes water/binder (-).

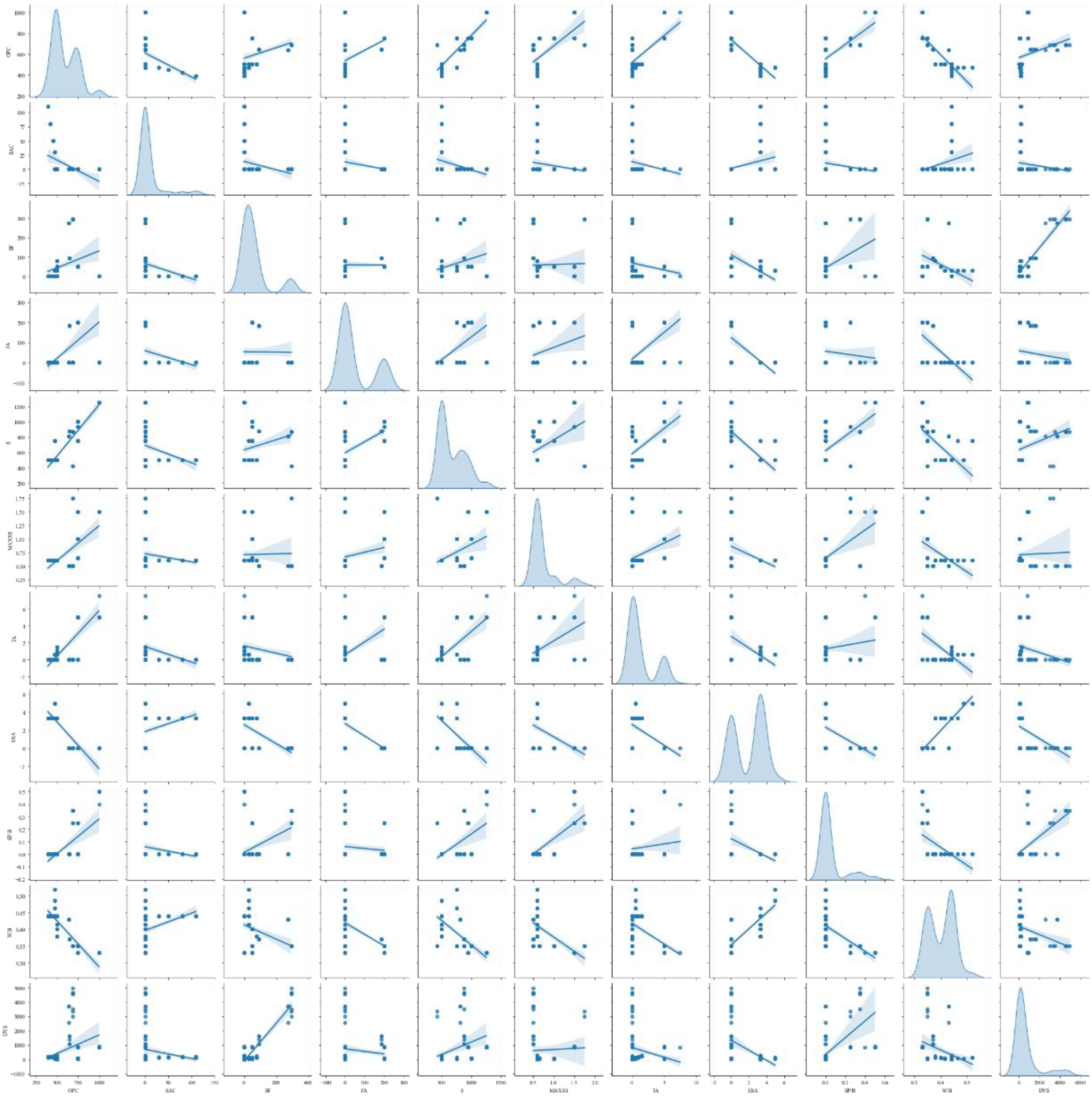


Fig. 1 Pair diagrams for predicting DYS

# 4. Modeling process

## 4.1 Hyperparameter selection

Fig. 2 depicts the process of tuning the RF model hyperparameters using GA. As can be seen from the figure, for the DYS prediction, the *RMSE* value steadily decreases throughout the optimization process. In this case, the GA-RF model completes convergence at 32 iterations. At 50 iterations, the *RMSE* is 138.70 Pa. Table 2 lists the optimal RF hyperparameters determined by the GA-RF model.

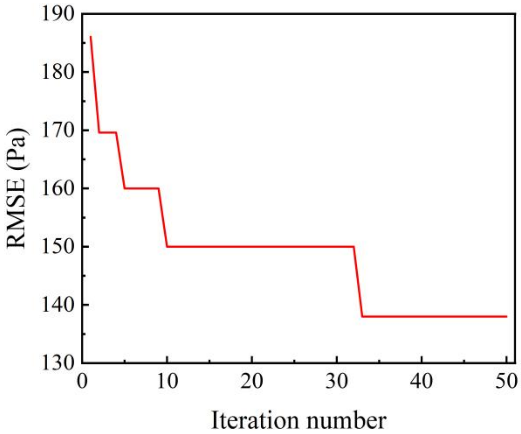


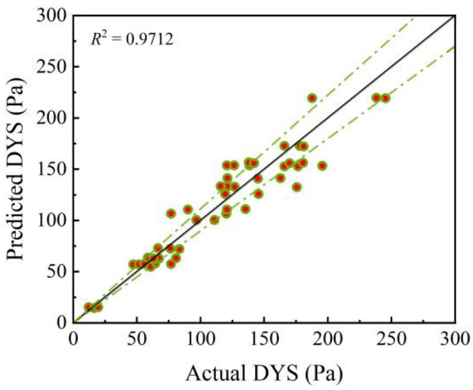

Fig. 2 Hyperparameters tuning process

Table 2. The optimal hyperparameters of the GA-RF model.

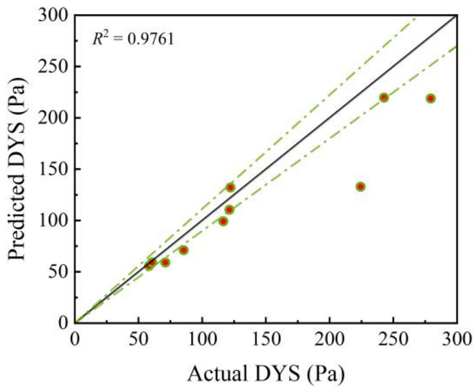
| Hyperparameters | Predicted targets |
|---|---|
| Max_depth | 12 |
| Min_samples_split | 3 |
| Min_samples_leaf | 2 |
| Max_DT | 567 |
| Max_features | 0.589 |

### 4.2 Prediction result

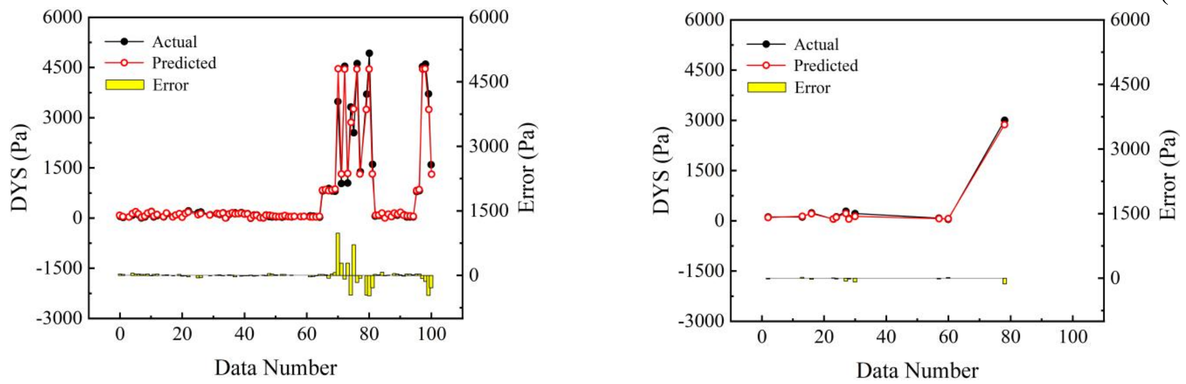
The prediction results of 3D printing concrete DYS are shown in Fig. 3. From the figure, it can be seen that the $R^2$ of the training set and testing set of the DYS prediction model are 0.9712 and 0.9761, respectively, in which the error of 89% of the data is less than 10%. This shows that the error of the prediction model is small and the accuracy is high. Table 3 presents the evaluation results of the GA-RF model training and testing performance. As can be seen from the table, the GA-RF model has lower *MAE* and *RMSE* values on both the training and testing sets, again demonstrating its higher prediction accuracy.




(a)




(b)




(c) (d)

Fig. 3 Comparison between predicted and actual HE values: (a) Correlation on the training set; (b) Correlation on the testing set; (c) Error on the training set; (d) Error on the testing set

Table 3. Evaluation results of the GA-RF model on training and testing sets.

| Models | $R^2$ | *MAE* | *RMSE* |
|---|---|---|---|
| Training | 0.97 | 77.85 | 191.23 |
| Testing | 0.98 | 42.71 | 61.86 |

## 5. Importance analysis

Fig. 4 demonstrates the importance of the influence of each input parameter on the DYS. As can be seen from the figure, the first six most important parameters are SF, MAXSS, SP/B, S, OPC, and W/B. FA, ESA, and TA have a slightly smaller effect on DYS, while the effect of SAC is almost negligible. This is mainly because the main components of SF are colloidal substances such as $SiO_2$ and $CaSiO_3 \cdot nH_2O$, which can fill the microporous and fine pores in concrete, improve the skeletal structure of concrete, promote the hydration reaction of cement, and thus improve the DYS of concrete [24]. The change of MAXSS will lead to the change of porosity and skeleton structure in concrete, which will affect the compactness and strength of concrete, thus affecting the DYS of concrete. Generally speaking, the smaller the MAXSS, the better the compactness of concrete, the higher the strength, and the higher the DYS [24]. In addition, the addition of SP can increase the fluidity of concrete, and reduce the viscosity and internal friction of concrete, thus reducing the frictional resistance inside the concrete and making the internal stress of concrete more uniform, thus improving the DYS of concrete. At the same time, SP can also reduce the pores and voids in concrete and improve the compactness and strength of concrete, further improving the DYS of concrete [25]. While suitable doses of OPC, S, and water can enhance the bonding between cement particles, thus improving DYS [26].

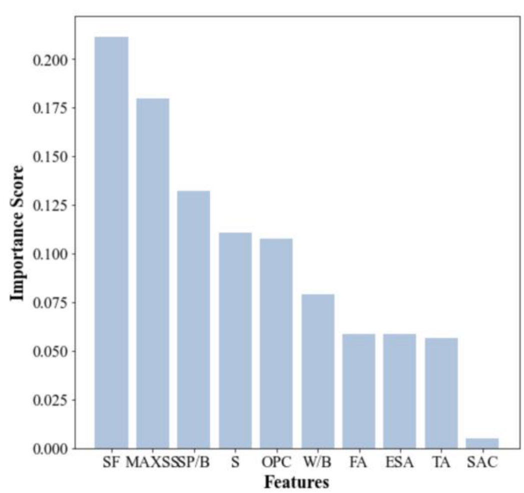



Fig. 4 Importance analysis results

## 6. Conclusion

In this study, a theoretical framework for predicting the DYS of 3D printing concrete is proposed. The results show that the proposed GA-RF model for predicting the DYS of 3D printing concrete has high prediction accuracy with $R^2$ of 0.9712 and 0.9761 for the training and testing sets, respectively, with 89% of the data having an error of less than 10%. The importance analysis shows that the top six input features that contribute most to the output DYS are SF, MAXSS, SP/B, S, OPC, and W/B. The effects of FA, ESA, and TA on DYS are slightly smaller, while the effects of SAC are almost negligible. The research results can help designers to better understand the mechanical properties and deformation laws of 3D printing concrete, to design the structure and shape of 3D printing parts more accurately and improve their performance and reliability. The research can also provide theoretical references for the application and promotion of 3D printing technology and machine learning technology in civil engineering. In addition, the results of this study can also provide references and insights for research in other related fields. For example, in the fields of building materials and structural mechanics, researchers can also use similar methods to explore the mechanical properties and deformation patterns of materials. Based on this, the formulation and structure of the materials can be further optimized to improve their performance and reliability.

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