Artificial Intelligence Techniques in Concrete

Subjects: Computer Science, Artificial Intelligence

Contributor: Fatima Alsaleh , Mohammad Bassam Hammami , George Wardeh , Feras Al Adday

Due to the speed of artificial intelligence (AI) techniques in solving engineering problems, there has been a tendency to use these techniques in various fields of civil engineering, including designing construction materials (concrete mixtures for example) or estimating their properties. As it is hard to predict the compressive strength of concrete due to the different nonlinearities inherent in the mixture designs, various concrete companies are continuously looking to use new methods and technologies to predict the compressive strength. Such methods include numerical modelling and artificial intelligence due to their advantages.

concrete   binary particle swarm algorithm   artificial neural networks

1. Introduction

To determine the strength of concrete mixtures using the traditional approach, the following steps are required: (1) Identify the components of the mixture, such as the types and amounts of sand, gravel, cement, and auxiliary materials. (2) Determine the correct amount of water to add to the mix, considering local evaporation factors. (3) Implement the mix using appropriate procedures and steps, considering ambient temperature and humidity. (4) Fill molds with the mixture according to the prescribed shapes and dimensions. (5) Allow the mixture to harden and form a concrete base by leaving it inside the mold for 7 to 28 days. (6) Extract the concrete beam from the mold and expose it to external forces using special testing devices to determine its compressive strength. (7) After completing the experiments, remove any waste resulting from the examination process [1][2][3][4][5].

Due to the speed of artificial intelligence (AI) techniques in solving engineering problems, there has been a tendency to use these techniques in various fields of civil engineering, including designing construction materials (concrete mixtures for example) or estimating their properties. As it is hard to predict the compressive strength of concrete due to the different nonlinearities inherent in the mixture designs, various concrete companies are continuously looking to use new methods and technologies to predict the compressive strength. Such methods include numerical modelling and artificial intelligence due to their advantages. These methods are efficient and environmentally friendly, as there is no waste in the testing process. In addition, they are more economical since there is no need for test means, test materials, or even laboratory employees. Moreover, these methods are flexible since many parameters can be taken into consideration, along with the speed of their implementation. It is crucial to accurately predict and evaluate the compressive strength of concrete mixtures, as it is one of the most important features of concrete [6][7].

Several recent studies focused on evaluating compressive strength using machine learning (ML) practices [8] which involve regular, big, and complete information. However, collecting this information is restricted due to the lack of data corresponding to the diverse input characteristics [9]. The concept of utilizing particle swarm optimization (PSO) begins by resetting particles within the search space randomly. Then, the particles construct upon their previous successful attempts and those of their neighbors to discover the optimal particle state. This is achieved by resetting the particle's location and updating its velocity [10]. Furthermore, the parameters of PSO can be easily modified, making it suitable for a wide range of practical problems [11]. In simpler terms, particle velocity in each cycle is determined by three factors: (1) the particle's current location, (2) the best location it has ever been, and (3) the best location within the entire group. This concept is explained in greater detail in reference [12]. PSO is a widely used procedure in the field of Swarm Intelligence that relies on optimization [13]. The goal of the optimization process is to find the best possible solutions to specific problems while taking into account any relevant constraints [14].

2. Artificial Swarm Intelligence in Civil Engineering

Concrete has several advantageous characteristics, including high wear resistance, low water permeability, and good compressive strength, and it is widely used in civil structures [15][16][17][18]. To maintain resident safety and structure durability, construction engineers are mainly concerned with the quality of building materials, notably the compressive strength of concrete. One typical method of evaluating the concrete's other physical and mechanical characteristics is measuring its compressive strength, which acts as a significant and trustworthy indicator of whether or not a concrete mixture conforms with engineering design criteria [16][17]. The process of precisely measuring the compressive strength of concrete mixtures is difficult, time-consuming, and associated with multiple problems [18][19][20]. Although statistical and experimental models incorporate a lot of data from laboratory tests, the results' accuracy is still poor [20].

Artificial intelligence models (AIMs) have been proposed as an alternative method to address the challenges of compressive strength prediction connected to the impact of various mixed design parameters [21][22][23][24][25][26]. By predicting the compressive strength of the concrete, a project's time and expense can be reduced. As a result, AIMs can be used to identify this important characteristic [27].

A mathematical model for estimating the compressive strength of concretes with additives was developed by Kandiri et al. [28] using an artificial neural network (ANN) technique. In the testing phase, the proposed model showed acceptable accuracy with a mean absolute percentage error of 11.10%. Ngo et al. [29] used artificial neural networks (ANNs), support vector regression (SVR), linear regression (LR), and M5P techniques for the prediction of axial strength in circular steel tube confined concrete columns. The authors outlined key distinctions between the techniques and concluded that the M5P was the best artificial intelligence (AI) model for predicting experimental results when compared to others. Goutham and Singh [30] used support vector regression (SVR) to predict the compressive strength of concrete. By comparing the analytical results with those of a non-destructive test, the authors concluded that SVR can be successfully used to predict the compressive strength of concrete.

Using four artificial intelligence models (AIMs), namely ICA-XGBoost, AIM ICA-ANN, ICA-SVR, and ICA-ANFIS, Duan et al. [31] evaluated the compressive strength of concrete made by recycled aggregates. The ICA-XGBoost model is the best one for determining the compressive strength of concrete, according to the findings. According to the authors, the proposed method can be used to verify that recycled concrete has the required mechanical characteristics in structural engineering [31].

Another study by H. N. Muliauwan et al. [32] determined the most exact Input/Output (I/O) connections between the components of concrete mixtures by employing many AIMs. The three AIMs employed in this investigation were support vector machines, linear regression, and artificial neural networks. The simulation's results using roughly 1030 compressive strength test values demonstrated that AIMs can facilitate the development of precise predictive models for concrete properties without the need for substantial expenditures on costly laboratory experiments.

Using six different types of AIMs, Cihan [27] employed AI to forecast the compressive strength of concrete. The adopted techniques were linear regression, classification and regression trees, K-nearest neighbor and extreme learning machine, adaptive neuro-fuzzy inference system (ANFIS), random forest, and SVR. The correlation factor, absolute mean error, root mean squared, and mean were used as standards to evaluate the efficiency of these approaches. Comparative results showed that the ANFIS outperforms the competition as a prediction model. The findings of the random forest model were nearly identical to those of the ANFIS, while the classification and regression tree had the lowest level of correctness. To estimate compressive strengths, Nafees. et al. [33] used three models namely genetic programming (GEP), ANFIS, and MLPNN that is a form of ANN. The results of the study showed that GEP models for data predictions are more precise than machine learning (ML) and that a new mathematical formula might be created and utilized to estimate additional database properties. The strength of lightweight concrete was predicted by Kumar et al. [25] using six machine learning algorithms: GPR, EL, SVMR, enhanced SVMR and GPR, and ensemble learning (EL). The results of this research showed that the optimized GPR model had the greatest accuracy. Furthermore, the improved GPR and SVMR models showed excellent behavior. K. Nasrollahzadeh and E. Nouhi, 2016 [34], applied the fuzzy inference model to improve a new precise procedure and to evaluate the square concrete columns' strength and strain subjected to a vertical load strengthened by fiber polymer wraps. An experimental compressive strength of 261 and a crucial experimental strain of 112 were gathered from the previous studies. The outputs of the finally proposed (Takagi–Sugeno) fuzzy inference models were well agreed with the experimental data of both strain and strength [34].

References

1. Concrete Mix Design Technician Study Guide; North Carolina Division of Highways, Materials and Tests Unit: Raleigh, NC, USA, 2019.
2. Giatec Scientific Lnc. Concrete Mix Design Just Got Easier. Available online: www.Giatecscientific.com/author/admin/ (accessed on 20 June 2023).

3. Al Adday, F.; Awad, A. Pre-wetting of recycled concrete as alternative of chemical, natural and industrial waste additives. Int. J. Innov. Technol. Explor. Eng. 2019, 8, 743–748.
4. Al Adday, F. Fresh and hardened properties of recycled concrete aggregate modified by iron powder and silica. Int. J. Geomate 2019, 16, 222–230.
5. Awad, A.; Al Adday, F.; Qasem, A.; Al-Dulaimy, A. An Experimental Study on the Possibility of Demolition of Destroyed Concrete Buildings with Different Types of Acid. Int. J. Eng. Res. Technol. 2020, 13, 2297–2304.
6. Li, H. Prediction of high-performance concrete compressive strength through novel structured neural network. J. Intell. Fuzzy Syst. 2023, 45, 1791–1803.
7. Van Damme, H. Concrete material science: Past, present, and future innovations. Cem. Concr. Res. 2018, 112, 5–24.
8. Golafshani, E.M.; Behnood, A.; Arashpour, M. Predicting the compressive strength of eco-friendly and normal concretes using hybridized fuzzy inference system and particle swarm optimization algorithm. Artif. Intell. Rev. 2022, 56, 7965–7984.
9. Lyngdoh, G.A.; Zaki, M.; Krishnan, N.A.; Das, S. Prediction of concrete strengths enabled by missing data imputation and interpretable machine learning. Cem. Concr. Compos. 2022, 128, 104414.
10. Azam, A.; Bardhan, A.; Kaloop, M.R.; Samui, P.; Alanazi, F.; Alzara, M.; Yosri, A.M. Modeling resilient modulus of subgrade soils using LSSVM optimized with swarm intelligence algorithms. Sci. Rep. 2022, 12, 14454.
11. Zhu, J.; Liu, J.; Chen, Y.; Xue, X.; Sun, S. Binary Restructuring Particle Swarm Optimization and Its Application. Biomimetics 2023, 8, 266.
12. Mahdavi, G.; Nasrollahzadeh, K.; Hariri-Ardebili, M.A. Optimal FRP Jacket Placement in RC Frame Structures Towards a Resilient Seismic Design. Sustainability 2019, 11, 6985.
13. Mohd Yamin, M.N.; Ab. Aziz, K.; Siang, T.G.; Ab. Aziz, N.A. Particle Swarm Optimisation for Emotion Recognition Systems: A Decade Review of the Literature. Appl. Sci. 2023, 13, 7054.
14. Van Zyl, J.-P.; Engelbrecht, A.P. Set-Based Particle Swarm Optimisation: A Review. Mathematics 2023, 11, 2980.
15. Baron, J.; Olivier, J.-P. Les Bétons: Bases et Données Pour Leur Formulation; Eyrolles: Paris, France, 1996.
16. Ghali, A.; Favre, R.; Elbadry, M. Concrete Structures: Stresses and Deformations: Analysis and Design for Serviceability, 3rd ed.; Spon Press: London, UK, 2002.

17. Brandt, A.M. Cement-Based Composites: Materials, Mechanical Properties and Performance; CRC Press: Boca Raton, FL, USA, 2005.
18. Smarzewski, P. Mechanical and Microstructural Studies of High Performance Concrete with Condensed Silica Fume. Appl. Sci. 2023, 13, 2510.
19. Beskopylny, A.N.; Stel'makh, S.A.; Shcherban', E.M.; Mailyan, L.R.; Meskhi, B.; Chernil'nik, A.; El'shaeva, D.; Pogrebnyak, A. Influence of Variotropy on the Change in Concrete Strength under the Impact of Wet–Dry Cycles. Appl. Sci. 2023, 13, 1745.
20. Torrenti, J.M.; Reynouard, J.M.; Pijaudier-Cabot, G. Mechanical Behavior of Concrete; ISTE Ltd.: London, UK, 2010.
21. Xiao, Q.; Li, C.; Lei, S.; Han, X.; Chen, Q.; Qiu, Z.; Sun, B. Using Hybrid Artificial Intelligence Approaches to Predict the Fracture Energy of Concrete Beams. Adv. Civ. Eng. 2021, 2021, 6663767.
22. Wang, Y.R.; Lu, Y.L.; Chiang, D.L. Adapting Artificial Intelligence to Improve In Situ Concrete Compressive Strength Estimations in Rebound Hammer Tests. Front. Mater. 2020, 7, 8870.
23. Sharma, J.; Singhal, R.S. Comparative research on genetic algorithm, particle swarm optimization and hybrid GA-PSO. In Proceedings of the 2015 2nd International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, India, 11–13 March 2015; pp. 110–114.
24. Hassan, R.; Cohanim, B.; de Weck, O.; Venter, G. A Comparison of Particle Swarm Optimization and the Genetic Algorithm. In Proceedings of the 46th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference, Austin, TX, USA, 18–21 April 2005; American Institute of Aeronautics and Astronautics: Reston, VA, USA, 2005.
25. Kumar, A.; Arora, H.C.; Kapoor, N.R.; Mohammed, M.A.; Kumar, K.; Majumdar, A.; Thinnukool, O. Compressive Strength Prediction of Lightweight Concrete: Machine Learning Models. Sustainability 2022, 14, 2404.
26. Rezvan, S.; Moradi, M.J.; Dabiri, H.; Daneshvar, K.; Karakouzian, M.; Farhangi, V. Application of Machine Learning to Predict the Mechanical Characteristics of Concrete Containing Recycled Plastic-Based Materials. Appl. Sci. 2023, 13, 2033.
27. Cihan, M.T. Comparison of artificial intelligence methods for predicting compressive strength of concrete. Građevinar 2021, 73, 617–632.
28. Kandiri, A.; Golafshani, E.M.; Behnood, A. Estimation of the compressive strength of concretes containing ground granulated blast furnace slag using hybridized multi-objective ANN and salp swarm algorithm. Constr. Build. Mater. 2020, 248, 118676.

29. Ngo, N.-T.; Pham, T.-P.-T.; An, L.H.; Nguyen, Q.-T.; Nguyen, T.-T.-N.; Huynh, V.-V. Prediction of axial strength in circular steel tube confined concrete columns using artificial intelligence. J. Sci. Technol. Civ. Eng. HUCE 2021, 15, 10.
30. Goutham, S.J.; Singh, V.P. Artificial Intelligence for Compressive Strength Prediction of Concrete. IOP Conf. Ser. Mater. Sci. Eng. 2020, 1004, 12010.
31. Duan, J.; Asteris, P.G.; Nguyen, H.; Bui, X.-N.; Moayedi, H. A novel artificial intelligence technique to predict compressive strength of recycled aggregate concrete using ICA-XGBoost model. Eng. Comput. 2021, 37, 3329–3346.
32. Muliauwan, H.N.; Prayogo, D.; Gaby, G.; Harsono, K. Prediction of Concrete Compressive Strength Using Artificial Intelligence Methods. J. Phys. Conf. Ser. 2020, 1625, 12018.
33. Nafees, A.; Javed, M.F.; Khan, S.; Nazir, K.; Farooq, F.; Aslam, F.; Musarat, M.A.; Vatin, N.I. Predictive Modeling of Mechanical Properties of Silica Fume-Based Green Concrete Using Artificial Intelligence Approaches: MLPNN, ANFIS, and GEP. Materials 2021, 14, 7531.
34. Nasrollahzadeh, K.; Nouhi, E. Fuzzy inference system to formulate compressive strength and ultimate strain of square concrete columns wrapped with fiber-reinforced polymer. Neural Comput. Applic. 2018, 30, 69–86.