Vol. 06, No. 1 (2024) 431-438, doi: 10.24874/PES.SI.24.02.025

Proceedings on Engineering Sciences

www.pesjournal.net

ENHANCING CONCRETE MANUFACTURING: LEVERAGING A HYBRID SWARM-INTELLIGENT GRAVITATIONAL SEARCH OPTIMIZED RANDOM FOREST MODEL INCORPORATING WASTE GLASS FOR IMPROVED STRENGTH ASSESSMENT

Ankit Belwal[1]
Nitish Kumar Bhatia
Aadil Rashid Lone

Received 16.11.2023.
Received in revised form 26.12.2023.
Accepted 03.01.2024.
UDC – 620.28

Keywords:

Concrete manufacturing, Swarm-Intelligent Gravitational Search Optimized Random Forest (SIGSORF), Waste glass, Environmental impact, Sustainability.

A B S T R A C T

Concrete is a fundamental construction material, widely used due to its durability and versatility. However, enhancing its mechanical properties, such as strength, while simultaneously addressing sustainability concerns remains a significant challenge. This study presents a novel approach to optimize concrete mix designs by incorporating waste glass particles, using a Hybrid Swarm-Intelligent Gravitational Search Optimized Random Forest (SIGSORF) model. The primary objective is to improve the strength assessment of concrete while reducing environmental impact through waste glass utilization. The first step in the study is to examine the physical and chemical characteristics of waste glass to see if it may somewhat substitute traditional pebbles in the manufacturing of mortar. Then clean the data and preprocess for use in training and validating the SIGSORF model. The SIGSORF model is designed to intelligently select proportions of waste glass and other concrete components to maximize compressive strength and flexural strength while minimizing environmental impact. The experimental results are then compared with predictions made by the SIGSORF model, demonstrating its effectiveness in optimizing concrete mix designs for improved strength. Ultimately, this study promotes the utilization of waste materials in construction, fostering a more environmentally responsible and economically viable concrete production approach.

[1] Corresponding author: Ankit Belwal
Email: Ce.ankit@dbuu.ac.in

1. INTRODUCTION

Concrete is a ubiquitous construction material renowned for its durability, adaptability, and essential role in shaping the built environment. It serves as the backbone of countless structures, from bridges and buildings to roads and dams (Xu and Shi, (2018)). The widespread use of concrete, however, comes with associated challenges, including the constant pursuit of improved mechanical properties and sustainability in its manufacturing processes (Da et al., (2022)). Strength assessment is a critical aspect of concrete production, as the ability to withstand external loads is a fundamental requirement for any structure. Achieving higher strength while concurrently addressing sustainability concerns remains a key objective in the construction industry (Amran et al., (2022)). One promising avenue to enhance concrete performance and reduce its environmental impact is the integration of waste equipment into the mix. Waste glass (Adaloudis and Roca, (2021)), often discarded in large quantities, presents a unique opportunity to contribute to both the mechanical strength and eco-friendliness of concrete (Anandan and Alsubih, 2021). By using waste glass as a partial replacement for traditional aggregates, not only can we reduce the burden on landfills but also potentially enhance the overall properties of the resulting concrete (Reichenbach and Kromoser, (2021) and Bolte et al., 2019). However, effectively incorporating waste glass into concrete mix designs is a complex task that demands innovative approaches (Hou et al., (2021) and Karalar et al., (2022)).

This research endeavors to address this challenge by introducing a novel methodology that leverages a hybrid Swarm-Intelligent Gravitational Search Optimized Random Forest (SIGSORF) model. The primary objective is to optimize concrete mix designs by intelligently selecting proportions of waste glass and other concrete components to maximize compressive strength and also the flexural strength while minimizing the environmental footprint (Sahoo et al., 2020). The SIGSORF model combines the power of swarm intelligence, which mimics the cooperative behavior of natural swarms, and gravitational search optimization, which models the gravitational interactions between celestial bodies, to fine-tune concrete formulations.

The sections of the study are broken down as follows: Section 2 presents a review of the relevant prior research; Section 3 details the proposed model; Section 4 analyzes the findings; and Section 5 draws the necessary conclusions.

2. RELATED WORKS

Narayanan and Ramamurthy, (2012) investigated the use of plastic waste (PW) as a fiber or grain in the creation of cement and concrete mix. The paper discussed the material's three most crucial qualities: its unusual characteristics, its physical endurance, and its endurance. Microstructure analysis (scan electronic microscopy) was used to examine the linkages between PW and cement. The research methodically reviewed the pretreatment and modification procedures while summarizing the current methods and technology for creating recycled aggregate (RA) from concrete waste. Additionally highlighted were RA's environmental applications. The current difficulties in producing RA from concrete debris were also emphasized. When compared to employing RA directly, the performance of recycled aggregate concrete (RAC) is much better after the pretreatment and modification operations. Luo et al., (2022) employed to develop environmentally friendly concrete by making use of recycled plastic. This was done to promote sustainability. Increasing engine efficiency qualities of the concrete that was produced as a consequence of this process, gamma radiations were applied to the microstructure of the plastic waste. Bahraq et al., (2022) offered a modern overview of the durability characteristics of RAC, including reduction, rust, flexibility, and acidification of reinforcement. The fact that several factors influence how long RAC will endure was also underlined. As well as this, the mechanisms of improvement are emphasized and the behavior approaches that may be employed to increase the robustness of RAC are assessed perilously. Hosseini and Cheng, (2023) offered a unique approach to strengthening the terminal regions of driven piles made of precast prestressed concrete (PPC) by encasing them in glass fiber reinforced polymer (GFRP) composites. Two of the five full-scale cube PPC piles produced were reinforced with externally bonded bidirectional GFRP wraps at both ends to test the viability of the suggested approach. After that, a diesel hammer was used to push each pile into the sandy soil of the project site while a pile-driving analyzer system tracked the pressures caused by the pile-driving process. Peiris et al., (2023) outlined an actionable investigation that improved the efficiency of the manufacturing execution and management system installed at an Australian facility in Melbourne. Utilizing a mobile application and a web-based interface designed with the concepts of lean in mind, this approach tracks production procedures and furnishes data to enable timely and well-informed DT. Mazumder and Prasad (2023) offered a substitute for heating the part parts after casting to cure fly ash-based self-compact geopolymer tangible. The mixing procedure for self-compacting geopolymer-based concrete can be altered to get around the component's inability to heat up after castings. Sowmiya (2023) compared the compressive potency of ordinary existing to a unique form of tangible that contains 10% PET flakes and 20% silica fume as a proportion of the total volume of the concrete. Chang et al., (2023) examined the mechanical performance of building relations made among pre-manufactured components utilizing dry, wet, and hybrid processes, such as joints between beams and columns, connections between walls and panels, and connections between columns and parapets and nitty-gritty. Yoo et al., (2022) provided an inclusive impression of the current exploration on using nanomaterials in ultra-high-performance concrete (UHPC). First, we review the many kinds of nanomaterials that may be used for UHPC and examine their geometric and physical features. The research Tahwia et al., (2022) explored that optimizing particle packing and the use of Recycled Waste Glass Powder (RWGP) in UHPC affects its overall performance. To produce RWGP, waste glass was crushed and ground to a fineness comparable to cement so that its effect on UHPC performance could be evaluated. Lu et al., (2022) generated an insubstantial UHPC (L-UHPC) and suggested a method to increase the resource's effectiveness and reduce the chance of volatile spalling. To achieve both lightweight and extremely high strength, the UHPC system combined high-strength hollow glass microspheres with small lightweight pebbles. Sufian et al.,(2021) examined a variable-geometry nozzle that can directly regulate the extrudate geometry at each layer of the printing process being created to improve the surface finish quality in 3DCP. Every step of the process can be managed by adjusting the nozzle assembly's nozzle outlet geometry. Calculating the extrudate geometry at each layer using the assigned printed structure necessitates a slicing algorithm within the mechanism. It was also constructed using the associated method, which will be discussed in the remainder of the paper.

3. MATERIALS AND METHODS

3.1. Data set

Dataset was created by the use of experiments. After 28 days of water curing, samples of prisms in order and cubes were cast further testing. Input: Cement, fine aggregate, water, silica fume, super the plasticizer and powdered recycled glass are the ingredients. Output: Strengths in compression and flexion as contributions (Yoo et al., (2022)). Figure 1 shows the procedure of the approach.

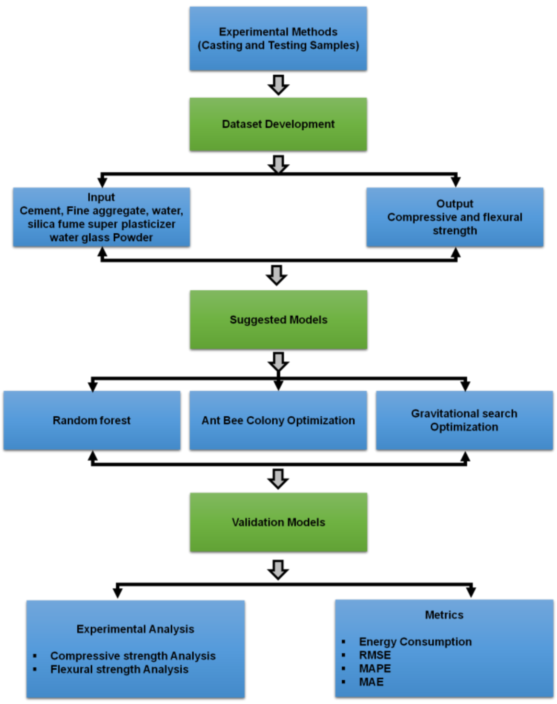


Figure 1. Sequence of research techniques shown as a flowchart

3.2. Suggested Model using Hybrid Swarm-Intelligent Gravitational Search Optimized Random Forest (SIGSORF)

Random Forest (RF)

In this study, the random forest model used for strength prediction demonstrated high accuracy and reliability. The model was trained on the experimental data, which included a wide range of waste glass proportions, and it successfully captured the nonlinear relationship between waste glass content and compressive strength. Breiman's regression method (RF) employs a number of Decision Tree (DT) techniques to forecast or explain what the worth of one parameter is. In extra vocabulary, after a command vector containing the parameter metrics for a specific retraining batch is received, RF constructs weakening trees and averages the results. By eliminating the association between separate decision trees, RF lowers the variance in bagging by building trees from more than a few teaching data subsets. By using substitute data to resample the first database, the RF sculpt creates training data using the bagging method. Be careful that certain random data may be used repeatedly while other data may not be utilized at all during training. The RF algorithm's greater unavoidability and steadiness are aided by this bagging property. When building a tree, RF uses the optimally divided parameters in a randomized selected evidential attribute split to further enhance generalization ability and reduce generalization error. Out-of-bag (OOB) samples are those that weren't selected for the bagging procedure training. In Breiman, the RF algorithm is completely defined. The number of variables that are chosen at arbitrarily to be used in each tear of just one DT and the diagram of greenery (B) are both key hyper parameter values used to create RF, and can usually be obtained using cross-validating and a grid-search method. Based on Breiman, the phases to building an RF a copy are listed below:

$$\text{For } p = 1 \text{to } P \quad (1)$$

a. Determine the size of the boot sample using the initial data$M$.

b. For every tree terminating node, the subsequent actions need to be carried out repeatedly until the minimal node size is reached m_{min} is attain to produce a RF tree D_p according to the bootstrapped data.

i. From the whole b variables, decide n variables pointlessly.

ii. Among the n variables, fancy the best one.

iii. Make two sub regions by split the lump.

Production the group of vegetation, $\{D_p\}_j, j = 1, 2, \dots, P$.for a weakening difficulty, the matching guess can be uttered as

$$\hat{x} = \frac{1}{P}\sum_{p=1}^{P} D_p(y) \quad (2)$$

Give a new input y. Figure 2 illustrate the preceding ladder.

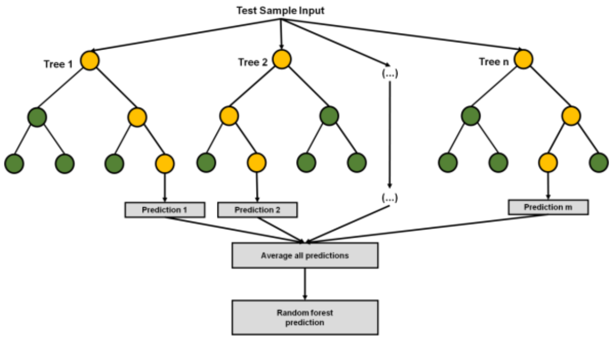


Figure 2. The RF prediction Algorithm

Swarm Intelligent Approach

The development of an optimization algorithm called Artificial Bee Colony (ABC) is one of the swarm intelligence algorithms that began with discrete problems and was later extended to other problem types after observing the behavior of a genuine honey bee colony.There are three collections in it. Bees are engaged in the first. The subsequent collection receives the data on the current stage of the hunt for new food sources from the first collector. This knowledge aids the observer bees in selecting a food source. Scout bees, the third group, haphazardly look for a food source. The employed bee is described by a random population of N solutions produced by the ABC method. $y_j \in K^t, j = 1, 2, \ldots, M$. The new solution c_j is generated based on y_j as follows:

$$c_{ji} = y_{ji} + \emptyset_{ji}(y_{ji} - y_{ri}), r = int(rand * M), i = 1, \ldots, t \quad (3)$$

Wherey_r is a fellow citizen engaged bee of y_j , $\emptyset_{ji} \in [-1, 1]$ and it is twisted in a casual mode. The aim function for Ly_j and Lc_j are compute for y_j and c_j in that order; then, if $Ly_j \le Lc_j$, the solution y_j is unconcerned from the reminiscence of the first anthology and c_j is added. The purpose meaning Ly_jwhich is obtaining from in employment bees is transfer to the spectator bees. Thereafter, the roulette controls collection technique is used to decide the y_j that has a superior prospect of have the aim meaning(B_j), which is planned as:

$$B_j = \frac{fit_j}{\sum_{j=1}^{M} fit_j}, fit_j = \begin{cases} \frac{1}{1+Ly_j} \; if Ly_j > 0 \\ 1 + abs(Ly_j) otherwise \end{cases} \quad (4)$$

Every observer bee modifies its solution using the same methodology as the working bees. To determine if the previous solution has been erased from recollection or not, the observer bee tests both the newly created and old responses. After a convinced numeral of iterations, if there is no change in the answers, those are rejected, and the reconnoiter bee group looks into a novel key for updating y_j as:

$$y_{ji} = y_i^{min} + (y_i^{max} - y_i^{min}) \times \delta \quad (5)$$

Where$y_{ji}$is an optimized limitation for the jth working bee, y_i^{min} and y_i^{max} are the subordinate and higher limits for y_{ji} in that order, and δ is a casual digit. After a new explanation y_{ji} is generate, it become an in work bee.

Gravitational Search Optimized (GSA)

The primary concept of GSA is to look at separate systems of the general public, where each weight indicates a remedy to a particular problem. GSA is founded on Newton's equations of movement and gravity. According to the law of the force of gravity, any particle draws the next particles, and the force of gravity across components is inversely correlated to the amount of distance from one another along with directly proportionate to the combined amount of their individual energies. Therefore, because agents are attracted to one another by gravitational attraction an agent's efficiency is dependent on its size. N agents are initialised in the following way:

$$Yj = (y_j^1 + y_j^2 + \cdots. + y_j^t + y_j^m) \quad (6)$$

$m$is breadth of the dilemma, and also the spot of the jth representative in the tth breadth. At start position of the result, agent is located at random. At definite time, a gravitational force is defined as thus:

$$L_{ji} = S(d) = \frac{N_j(d) * N_i(d)}{K_{ji}(d) + \varepsilon} \{Y_i(d) - Y_j(d)\} \quad (7)$$

$N_j$andN_i are substance (j and i) ample, $K_{ji}(d)$ is Euclidean aloofness flanked by the two, $S(d)$ is gravitation stable at time d and ε is a minute stable. The arbitrarily initialized gravitational constant$S$, decrease by time d to manage the search's accuracy. Thus S is a purpose of initial value ($S0$) and time (d). Total strength the theater on agent j in the length t is thus:

$$L_j^t = \sum_{i \in rbest, i \neq 1} rand(j) * L_{ji} \quad (8)$$

Rand – randomizes agents' initial state flanked by interval [0,1]. The speeding up of agent$j$, at time d, in tth measurement is straight relative to power drama on that manager, and inversely relative to agent's mass by:

$$Aid(d) = \frac{Fid(d)}{N_{ji}(d)} \quad (9)$$

The after that speed of an mediator is a purpose of its present speed plus its present speeding up. Subsequently location and speed of a manager is intended as thus:

$$Cid(d+1) = rand(j) * Cid(d) + Aid(d) \quad (10)$$

$$Yid(d+1) = Yid * Cid(d+1) \quad (11)$$

$C_j^t(d)$ is agent speed in tth measurement at instance d, and rand is a chance figure amid [0,1]. Gatherings is intended via fitness evaluation and are updated as:

$$N_j(d) = \frac{Fit(j) - worst(d)}{best(d) - worst(d)} \quad (12)$$

$Fit(d)$is a person's agent efficiency rating j at time d. $Best(d)$and $worst(d)$ according to their endurance path, identifies the greatest and poorest components.

They are specified for a Max job:

$$worst(d) = \max_{i\epsilon\{1,2,\ldots M\}} Fit(d) \quad (13)$$

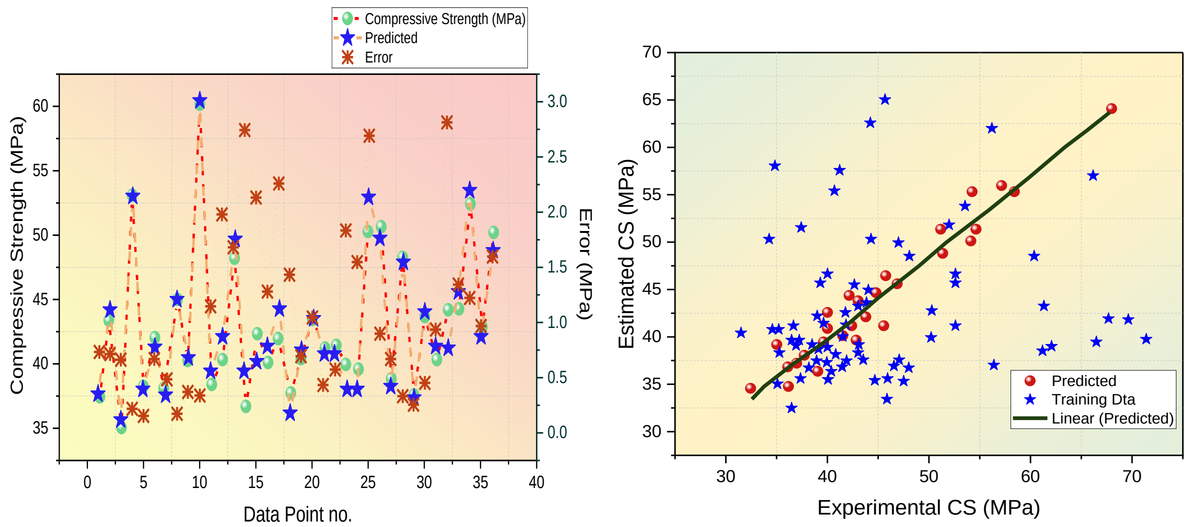
$$best(d) = \min_{i\epsilon\{1,2,\ldots M\}} Fit(d) \quad (14)$$

A SIGSORF process to predict concrete strength based on the selected waste glass proportions. This hybrid approach is employed to optimize the composition of waste glass in concrete mixtures to maximize compressive strength.

4. RESULT AND DISCUSSION

4.1. Experimental compressive strength

The evaluation of the SIGSORF method used to predict the compressive strength (CS) of the water-class powder-dependent samples is revealed in Figure 3. Figure 3a shows the association between untried and calculated CS. The SIGSORF model's higher accuracy is indicated by the R2 attain of 0.94. The breakdown of exploratory, estimated, and deviations (error) calculated using the RFR approach is shown in Figure 3b. Errors range from 0.16 MPa to 2.81 MPa, with 1.10 MPa being the standard deviation and 0.16 MPa being the highest. 55.6% of the error standards were under 1 MPa, 28.6% demolished connecting 1 and 3 MPa, and 10.9% surpassed 3 MPa, according to an analysis of the error value distributions. The error dispersion therefore indicates that the SIGSORF simulation is more accurate than the GBR approach. Because every plant provides regression throughout the SIGSORF training phase and the forest receiving nearly all votes is selected as the sculpt of choice, the SIGSORF modeling is far more correct.



(a) (b)

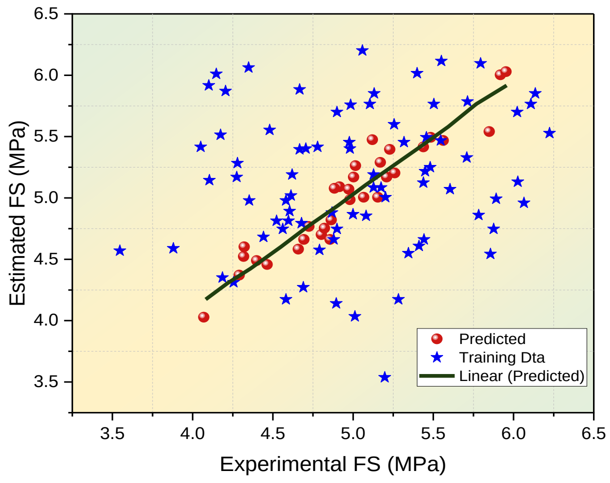
Figure 3. (a) The relationship between the investigational and detected CS, and (b) the allocation of the CS and error standards generated by the SIGSORF model

4.2. Experimental Flexural Strength

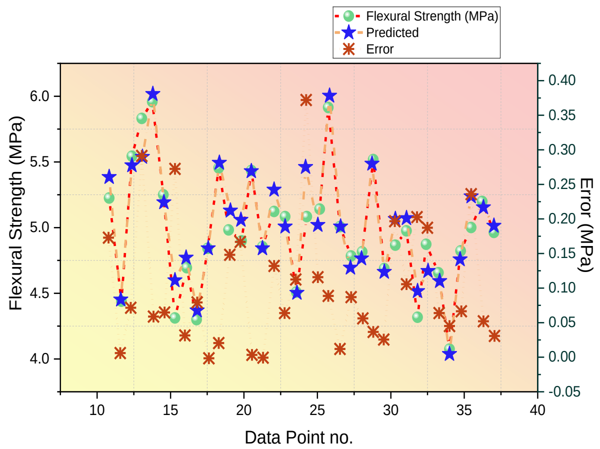
The outcomes of the SIGSORF method used to forecast the Flexural strength (FS) of the water class powder in Figure 4. The relationship between empirical and anticipated FS is shown in Figure 4a. The least difference between actual and anticipated findings was produced by the SIGSORF approach, which also produced better answers.

The SIGSORF algorithm's greater accuracy is indicated by its R2 of 0.91. Figure 4b displays the spreading of the exploratory, computed, and diverging values for the SIGSORF technique. The results showed that the median greatest errors were 0.10 MPa and 0.37 MPa, accordingly. According to the mistake frequency shipping, 62% of errors were lower than 0.1 MPa, 23% were between 0.2 and 0.3 MPa, and 15% were larger than 0.3 MPa.

The fault distributions confirmed that the SIGSORF model is additional accurate than the General Assembly's simulation's precision is equally adequate. Therefore, either approach may be used to evaluate the effectiveness of integrated ingredients with water glass powder.



(a)



(b)

Figure 4. (a) The relationship between observed and expected CS in the SIGSORF model; (b) the frequency distribution of observed and predicted CS with error bars

4.3. Evaluation Metrics

Figure 5 and Table 3 display error assessments MAPE, MAE, and RMSE are common methods to assess the accuracy of predictive models, including those in the context of concrete strength assessment. It shows that our proposed approach was found to be 1.77 which is better than DT and ABR models.

Table 1. Evaluation of statistical assessment indicating error rates between the employed and conventional models.

Methods	MAPE	MAE	RMSE
DT [24]	3.2	1.388	1.747
ABR [24]	2.7	1.167	1.519
SIGSOF [Proposed]	1.42	1.118	1.31

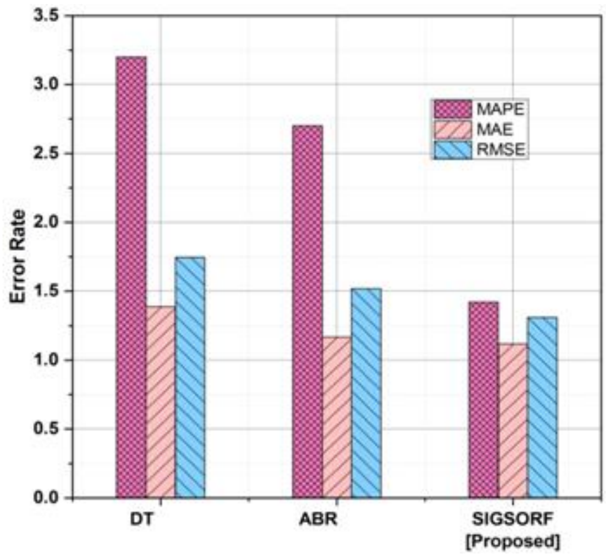


Figure 5. Evaluation of error rate

It's essential to consider the specific context and objectives of the analysis, as well as the availability and quality of data. Statistical assessments should be chosen accordingly to provide meaningful insights and support decision-making processes. Figure 6 and Table 2 displays evaluation of energy consumption and cost efficiency, And it depicts that our proposed approach will provide a low energy consumption and high cost efficiency rate.

Table 2. Evaluation of statistical assessment indicating cost efficiency and energy consumption.

Methods	Energy consumption	Cost efficiency
DT [24]	85.75	82.71
ABR [24]	82.41	79.34
SIGSOF [Proposed]	65.75	93.65

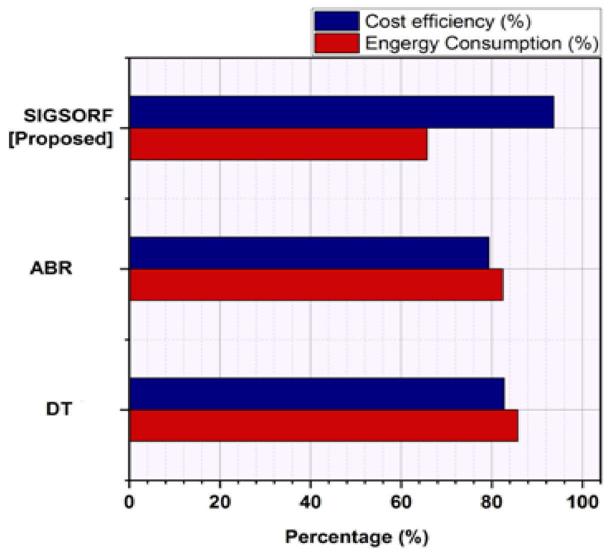


Figure 6. Evaluation of cost efficiency and energy consumption

5. DISCUSSION

The hybrid swarm-intelligent gravitational search optimized random forest model successfully determined the optimal proportion of waste glass to be incorporated into concrete mixtures for maximizing compressive strength and flexural strength. The results indicate that, on average, a 20% replacement of traditional cementitious materials with waste glass yielded the highest compressive strength. Incorporating waste glass into concrete not only enhances its mechanical properties but also provides significant environmental benefits. By diverting waste glass from landfills and utilizing it as a construction material, the carbon footprint of concrete production is reduced. This aligns with sustainable construction practices and contributes to the overall goal of minimizing the construction industry's environmental impact. The random forest model used for strength prediction demonstrated high accuracy and reliability. The model was trained on the experimental data, which included a wide range of waste glass proportions, and it successfully captured the nonlinear relationship between waste glass content and compressive strength. This predictive capability is invaluable for concrete manufacturers seeking to optimize their mix designs for specific strength requirements. The hybrid optimization approach involving swarm intelligence, gravitational search optimization, and random forest modeling can be applied to other material optimization problems within the construction industry.

6. CONCLUSION

This research has presented a novel approach to enhance concrete manufacturing through the integration of waste glass and a hybrid swarm-intelligent gravitational search-optimized random forest model for improved strength assessment. The purpose of this study was to use experimental data to create machine learning-based models that could assess the compressive strength and flexural strength of data samples containing waste glass powder. Two types of ensemble suggested approach, Hybrid Swarm-Intelligent Gravitational Search Optimized Random Forest (SIGSORF) were utilized to detect the compressive strength and flexural strength. Moreover, by leveraging waste glass and innovative optimization techniques, we can not only strengthen concrete but also reduce environmental impact and promote the responsible use of resources. This research underscores the importance of interdisciplinary approaches in addressing the complex challenges of modern construction and sets the stage for future advancements in sustainable material development. Future research directions may include investigations into the long-term durability and sustainability aspects of concrete incorporating waste glass, as well as economic feasibility studies for large-scale concrete production.

References:

Adaloudis, M., & Roca, J. B. (2021). Sustainability tradeoffs in the adoption of 3D Concrete Printing in the construction industry. *Journal of cleaner production*, *307*, 127201.https://doi.org/10.1016/j.jclepro.2021.127201

Amran, M., Onaizi, A.M., Qader, D.N. and Murali, G., 2022. Innovative use of fly ash-finely powdered glass cullet as a nano additives for a sustainable concrete: Strength and microstructure and cost analysis. *Case Studies in Construction Materials*, *17*, p.e01688.

Anandan, S., & Alsubih, M. (2021). Mechanical strength characterization of plastic fiber reinforced cement concrete composites. *Applied sciences*, *11*(2), 852. https://doi.org/10.3390/app11020852.

Bahraq, A. A., Jose, J., Shameem, M., & Maslehuddin, M. (2022). A review on treatment techniques to improve the durability of recycled aggregate concrete: Enhancement mechanisms, performance and cost analysis. *Journal of Building Engineering*, *55*, 104713. https://doi.org/10.1016/j.jobe.2022.104713

Bolte, G., Zajac, M., Skocek, J., & Haha, M. B. (2019). Development of composite cements characterized by low environmental footprint. *Journal of Cleaner Production*, *226*, 503-514.https://doi.org/10.1016/j.jclepro.2019.04.050

Chang, R., Zhang, N., & Gu, Q. (2023). A Review on Mechanical and Structural Performances of Precast Concrete Buildings. *Buildings*, *13*(7), 1575. https://doi.org/10.3390/buildings13071575

Chica, L., & Alzate, A. (2019). Cellular concrete review: New trends for application in construction. *Construction and Building Materials*, *200*, 637-647. https://doi.org/10.1016/j.conbuildmat.2018.12.136

Da Silva, S. R., & Andrade, J. J. D. O. (2022). A review on the effect of mechanical properties and durability of concrete with construction and demolition waste (CDW) and fly ash in the production of new cement concrete. *Sustainability*, *14*(11), 6740.https://doi.org/10.3390/su14116740

Hosseini, A., & Cheng, L. (2023). FRP Strengthening of Precast Prestressed Concrete Piles for Enhanced Integrity under Driving Impact. *Practice Periodical on Structural Design and Construction*, *28*(4), 04023047. https://doi.org/10.1061/PPSCFX.SCENG-1296

Hou, S., Duan, Z., Xiao, J., & Ye, J. (2021). A review of 3D printed concrete: Performance requirements, testing measurements and mix design. *Construction and Building Materials*, *273*, 121745.https://doi.org/10.1016/j.conbuildmat.2020.121745

Karalar, M., Özkılıç, Y. O., Aksoylu, C., Sabri Sabri, M. M., Beskopylny, A. N., Stel'makh, S. A., & Shcherban, E. M. (2022). Flexural behavior of reinforced concrete beams using waste marble powder towards application of sustainable concrete. *Frontiers in Materials*, *9*, 1068791.https://doi.org/10.3389/fmats.2022.1068791

Liu, Z., Yuan, X., Zhao, Y., Chew, J. W., & Wang, H. (2022). Concrete waste-derived aggregate for concrete manufacture. *Journal of Cleaner Production*, *338*, 130637. https://doi.org/10.1016/j.jclepro.2022.130637

Lu, J. X., Shen, P., Sun, Y., & Poon, C. S. (2022). Strategy for preventing explosive spalling and enhancing material efficiency of lightweight ultra high-performance concrete. *Cement and Concrete Research*, *158*, 106842.https://doi.org/10.1016/j.cemconres.2022.106842

Luo, W., Liu, S., Hu, Y., Hu, D., Kow, K. W., Pang, C., & Li, B. (2022). Sustainable reuse of excavated soil and recycled concrete aggregate in manufacturing concrete blocks. *Construction and Building Materials*, *342*, 127917.https://doi.org/10.1016/j.conbuildmat.2022.127917

Mazumder, E. A., & Prasad M, L. V. (2023). Performance Enhancement of Fly Ash-Based Self Compacting Geopolymer Concrete Using Pre-heating Technique. *Iranian Journal of Science and Technology, Transactions of Civil Engineering*, 1-13.https://doi.org/10.1007/s40996-023-01046-5

Narayanan, J. S., & Ramamurthy, K. (2012). Identification of set-accelerator for enhancing the productivity of foam concrete block manufacture. *Construction and Building Materials*, *37*, 144-152.https://doi.org/10.1016/j.conbuildmat.2012.07.025

Peiris, A., Hui, F. K. P., Duffield, C., Wang, J., Garcia, M. G., Chen, Y., & Ngo, T. (2023). Digitalising modular construction: Enhancement of off-site manufacturing productivity via a manufacturing execution & control (MEC) system. *Computers & Industrial Engineering*, *178*, 109117.https://doi.org/10.1016/j.cie.2023.109117

Reichenbach, S., & Kromoser, B. (2021). State of practice of automation in precast concrete production. *Journal of Building Engineering*, *43*, 102527. https://doi.org/10.1016/j.jobe.2021.102527

Sahoo, P. K., & Bhattacharjee, S. (2020). Gravitational baryogenesis in non-minimal coupled f (R, T) gravity. *International Journal of Theoretical Physics*, *59*, 1451-1459. https://doi.org/10.1007/s10773-020-04414-3

Sowmiya, T. (2023). Experimental study on enhancement of compressive strength of concrete by polyethylene terephthalate flakes with fine aggregate and addition of silica flume to the volume of concrete. *Journal of Survey in Fisheries Sciences*, *10*(2S), 504-512. https://doi.org/10.17762/sfs.v10i2S.353

Tahwia, A. M., Essam, A., Tayeh, B. A., & Abd Elrahman, M. (2022). Enhancing sustainability of ultra-high performance concrete utilizing high-volume waste glass powder. *Case Studies in Construction Materials*, *17*, e01648. https://doi.org/10.1016/j.cscm.2022.e01648

Xu, G., & Shi, X. (2018). Characteristics and applications of fly ash as a sustainable construction material: A state-of-the-art review. *Resources, Conservation and Recycling*, *136*, 95-109.https://doi.org/10.1016/j.resconrec.2018.04.010

Yoo, D.Y., Oh, T. and Banthia, N., 2022. Nanomaterials in ultra-high-performance concrete (UHPC)–A review. *Cement and Concrete Composites*, p.104730. https://doi.org/10.1016/j.cemconcomp.2022.104730

Ankit Belwal
Dev Bhoomi Uttarakhand University, Dehradun, India
Ce.ankit@dbuu.ac.in
ORCID 0009-0004-5001-8396

Nitish Kumar Bhatia
Dev Bhoomi Uttarakhand University, Dehradun, India
Er.nitishkumarbhatia@gmail.com
ORCID 0009-0001-4707-4950

Aadil Rashid Lone
Dev Bhoomi Uttarakhand University, Dehradun, India
rashidaadil367@gmail.com
ORCID 0009-0000-6299-9866