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Research Article

Impact of iron powder and blast furnace slag on the mechanical properties of polymer concrete: An experimental and hyperparameter-tuned ANN-based study

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ABSTRACT

Polymer-based materials have become increasingly used in concrete production and various engineering applications due to their versatile properties. In particular, polymer concrete (PC) has become a preferred reinforcement material in the construction industry. Various studies have been carried out to evaluate the performance of PC and to improve its mechanical properties by adding different admixtures. This study investigates the effects of fine materials such as iron powder (IP) and blast furnace slag (BFS) on the mechanical performance of PC. Within the scope of the study, samples with 5% and 10% IP, 5% and 10% BFS, 2.5% IP + 2.5% BFS and 5% IP + 5% BFS were prepared. These specimens were cured in the same laboratory environment and subjected to mechanical tests at the end of the 7th day. The results of the mechanical tests were compared to reveal the effect of fine materials on the performance of the PC. The potential of an artificial neural network (ANN) model is investigated to replicate real-world outcomes. The findings provide valuable insights into the potential of iron powder and blast furnace slag as admixtures to improve the mechanical properties of PC.

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1. Introduction

Polymer-based materials have become an increasingly preferred component in concrete production and various engineering applications in recent years. Polymer concrete (PC) is considered an important alternative to traditional concrete in the construction industry. The main reason for this is that PC has superior mechanical properties and chemical resistance, as well as advantages such as formability and fast curing. With these properties, PC finds a wide range of applications, especially in special construction projects and structures exposed to harsh environmental conditions. In addition to its mechanical strength and durability, PC is also recognized for its low permeability, which makes it highly resistant to water and chemical penetration. This property is particularly advantageous in environments where structures are exposed to aggressive chemicals, seawater, or other corrosive substances, thus extending the life of the material (Cakir et al. 2021; Ulu 2024). Furthermore, the lightweight of PC compared to conventional concrete can reduce the total dead-load on structures, making it a preferred option for rehabilitation projects or where weight reduction is critical.

The moldability of PC, allowing it to be adapted to different forms and shapes, further increases its appeal in architectural applications. This allows the creation of complex and aesthetically pleasing structures that would be difficult or costly to achieve with traditional concrete. The fast-curing time of PC is another key advantage as it provides faster project turnaround, which is beneficial in time-sensitive construction projects

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(Cakir 2022). Given these numerous advantages, research into improving the properties of PC has been extensive. Various studies have focused on improving its mechanical properties, durability, and overall performance through the incorporation of different admixtures and fillers. The addition of materials such as fibers, silica fumes, and fly ash has been investigated to optimize the performance of PC in different applications. In this context, research on the use of different additives to further improve the mechanical properties of PC is of great importance (Cakir et al. 2020, 2021; Cakir 2021; Ulu et al. 2022). In the literature, there are various studies on the PC. For example, Ulu (2024) explored the effect of resin proportion on the damping capacity of polymer concrete (PC), which is known for its fast setting, durability, and abrasion resistance. In this study, PC mixtures with varying resin proportions (11-19%) were tested using modal tests to measure natural frequency and damping ratios up to 1000 Hz. The findings revealed that the damping ratio decreased with resin content up to 17% but increased to 19%. Muthukumar and Mohan (2004) focused on the preparation and optimization of PCs using furan resin, silica aggregates, and micro filler. The combinations of these materials were designed using the design of experiments (DOE) approach, specifically aimed at minimizing voids in the mixture by optimizing the particle size distribution of high-purity silica fillers. A combined optimization was then performed to recommend a mix design that maximizes all mechanical properties. Cakir (2022) investigated the impact of curing time on the compressive and flexural strengths of the PC. The study tested 63 specimens at seven different ages (ranging from 1 day to 105 days) to observe the strength-time relationship. The results reveal that curing time significantly influences both compressive and flexural strengths. Notably, PCs achieve over 80% of their mechanical strength within the first three days, with minimal changes in long-term strength after 7 days. Omar et al. (2022) measured the impact of petroleum products, specifically gasoline and gas oil, on the mechanical properties of fiber-reinforced polymer concrete (FRPC). Four different polymer concrete mixes were prepared using epoxy resin as a binder, incorporating steel fibers (SF), glass fibers (GF), a combination of SF and GF, and a mix without fibers. After 28 days of curing, the samples were subjected to alternating cycles of submersion in gasoline and gas oil, followed by drying, over periods of 60, 90, 120, and 150 days. The study investigated properties such as compressive strength, splitting tensile strength, ultrasonic pulse velocity, dynamic elastic modulus, and total absorption, comparing the results with reference samples. The findings show that the mix with both SF and GF fibers exhibited the highest mechanical properties, with a 15% improvement over the reference mix.

In another work, Ulu et al. (2022) focused on the use of chopped glass fiber (CGF) reinforced PCs (CGFRPCs) and investigated the impact of excessive fiber reinforcement on the mechanical properties of the concrete. Six different mixtures, varying in CGF content (ranging from 0% to 1.0%), were prepared with reinforcing indexes (RIs) from 0 to 4. Tests on fresh concrete samples included setting times, peak temperature, and flow tests, while hardened concrete tests measured density, flexural strength, and compressive strength at various ages. The findings reveal that excessive fiber reinforcement negatively impacts both fresh and hardened concrete properties due to issues like fiber agglomeration, thixotropy, fiber pull-out, breakage, dislodged aggregate, and cracks in the interface and matrix. Cakir et al. (2020) examined the impact of Methyl Ethyl Ketone Peroxide (MEKP), a key catalyst, on the mechanical properties of the PC. Given the growing use and popularity of polymer materials in engineering applications due to their excellent properties, the study focuses on understanding how different amounts of MEKP affect the mechanical behavior of PC. Concerning the utilization of artificial intelligence in the prediction of property values in PCs, several studies have been conducted in this field, including those by Barbuta et al. (2012), Diaconescu et al. (2013), and Li et al. (2024a). Barbuta et al. (2012) predicted the compressive and flexural strength of the polymer concrete. In the study of Diaconescu et al. (2013), ANN modeling has successfully identified the optimal material composition to achieve peak values for compressive, flexural, and split tensile strengths. Deep neural networks (DNNs) are being employed to investigate the temperature-dependent mechanical behavior of concrete (Li et al. 2024a). Specifically, DNNs are being utilized to analyze the variation of Poisson's ratio, Young's modulus, specific heat, coefficient of thermal expansion, and thermal conductivity across a range of temperatures.

These literature studies focused on PCs and their mechanical properties. However, there is a limited number of studies investigating the effects of fine materials, especially industrial by-products such as iron powder (IP) and blast furnace slag (BFS), on polymer concrete. The distribution and interaction of fine materials in PC can significantly affect the overall performance of the concrete. Fine materials such as IP and BFS have attracted attention as potential admixtures in this context. Moreover, its environmental impact and contribution to sustainability have been investigated in various studies. A study has shown that when these industrial by-products replace cement at a certain rate, they improve concrete's surface resistance and compressive strength, thereby reducing the carbon emissions required to achieve a unit of compressive strength (Han et al. 2022). In their studies, Wang et al. (2024) observed that the utilization of such waste products results in lower carbon emissions compared to the use of ordinary Portland cement. In the study conducted by López-Ausín et al. (2024), it was observed that the use of by-products such as powdery ladle furnace slag led to a reduction in the carbon footprint. At higher added levels of this waste product, the magnitude of the reduction was more significant. By reusing these industrial wastes containing heavy metals without releasing them into the environment, the reclaimed areas can be reforested, reducing carbon dioxide and increasing the release of oxygen into the atmosphere. This approach mitigates environmental impact and contributes socially by benefiting the natural ecosystem (Li et al. 2024b). Therefore, to reduce global carbon emissions, it is crucial to minimize the waste products generated by the construction industry or repurpose them in different ways to contribute to green and sustainable development.

In this study, the effects of these materials on the mechanical performance of PC were investigated in detail. This study aims to fill this gap and to investigate in detail the effects of IP and BFS on the mechanical performance of polymer concrete. Within the scope of the study, PC specimens containing different proportions of IP and BFS were prepared and these specimens were cured under standard laboratory conditions and subjected to mechanical tests at the end of the 7th day (Cakir 2022). The aim was to determine the contribution of these fine materials to the strength and stiffness properties of polymer concrete. The results obtained provide valuable information for the development of new admixtures to improve the performance of polymer concrete. These findings provide an important contribution to the field of civil engineering from both academic and practical perspectives.

2. Materials and Methods

2.1. Materials

The primary components of PC include aggregates, binders, hardeners, and accelerators. In this study, quartz sands with sizes of 0.3–1 mm, 1–2 mm, 2–3 mm, and 3–5 mm were used. The chemical composition of these aggregates is provided in Table 1. A general-purpose polyester resin, known for its low volumetric shrinkage and minimal heat generation, was selected as the binder. The technical specifications of the resin, as supplied by the manufacturer, are shown in Table 2. For curing, Methyl Ethyl Ketone Peroxide (MEKP) was used, which is a standard catalyst for resins. Additionally, cobalt (1.5%) was chosen as an accelerator to enhance the effectiveness of the peroxide. Technical details for MEKP and cobalt can be found in Tables 3 and 4. In this study, the IP and BFS were obtained from a cast iron foundry in Turkey. The chemical components of the IP and BFS are illustrated in Fig. 1.

Table 1. Chemical composition of the aggregates.

Chemicals	0.3–1 mm	1–2 mm	2–3 mm	3–5 mm
SiO_2	98.86	94.15	94.15	94.15
SO_3	-	0.10	0.10	0.10
MgO	0.10	0.06	0.06	0.06
Na_2O	0.02	1.12	1.12	1.12
Fe_2O_3	0.148	0.46	0.46	0.46
CaO	0.01	0.39	0.39	0.39
K_2O	0.03	1.56	1.56	1.56
Al_2O_3	0.245	1.86	1.86	1.86
LOI	0.24	0.30	0.30	0.30

Table 2. Technical properties of the resin.

Properties	Values
Acid value	21.3 mg KOH/g
Flash point	33 °C
Exothermic temperature	158 °C
The liquid-solid ratio	64.6 %
Gel time	5.35 min
Viscosity	320 cP

Table 3. Technical properties of MEKP.

Properties	Values
Density	1.12 g/cm^3 (20 °C)
Viscosity	19 mPa.s (20 °C)
Water content	2.0 %
The free hydrogen peroxide content	2.2 %
Active oxygen	9.7 %
Ph	5.2
Gel time	18 min
Peak time	48 min
Self-accelerating decomposition temperature (SADT)	≥60 °C
Critical temperature (SADT)	65 °C
Flash point	>80 °C
Exothermic temperature	106 °C

Table 4. Technical properties of cobalt.

Properties	Values
Density	0.92 g/cm^3 (20 °C)
Viscosity	300 mPa s (20 °C)
Self-accelerating decomposition temperature (SADT)	≥150 °C
Flash point	62 °C
Cobalt content	6%

2.2. Preparation of PC mixtures

In the preparation of PC mixtures, the process began with the formulation of plain concrete samples. Initially, the granulometry curve of the aggregate was established to achieve an optimized gradation. Once the optimal gradation was determined, resin and cobalt were gradually incorporated into the aggregate mixture and blended using a mechanical mixer for 15 minutes. Subsequently, the MEKP was incrementally added to the mixture to ensure homogeneity. In the final stage, the MEKP was introduced into the mixture, which was then mixed for an additional 3 minutes with the mechanical mixer. Following the mixing process, the fresh PC was carefully placed into steel prism and cube molds, and the mix was compacted using an electronic shaking table (Fig. 2). The specimens were left in the molds until curing, and after demolding, they were cured in a laboratory environment at 20 ± 2 °C for 7 days. A total of three cubes, each measuring 40 mm x 40 mm x 40 mm, and three prisms, each measuring 40 mm x 40 mm x 160 mm, were produced from the plain PC (PPC).

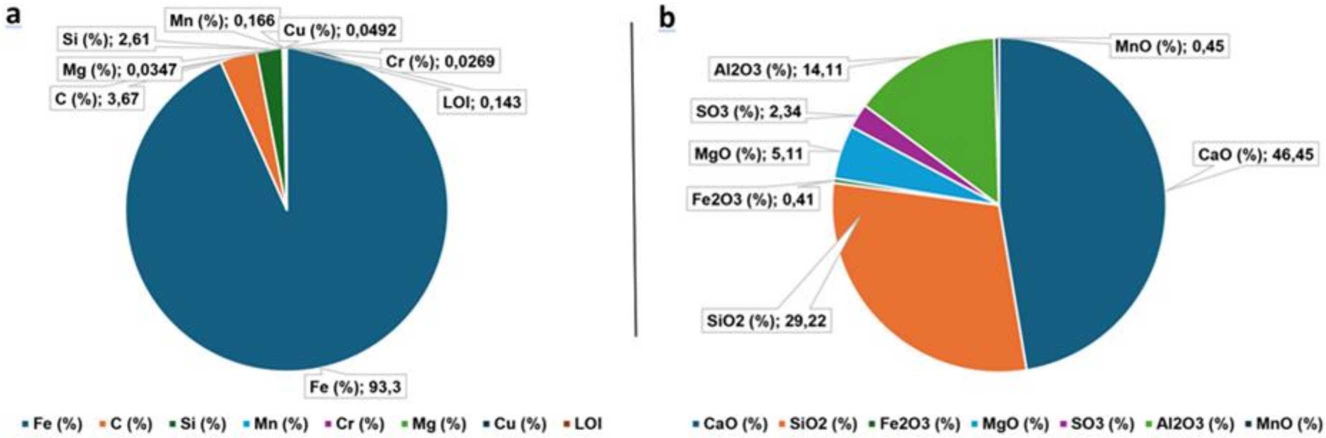

Fig. 1. Chemical components of: (a) IP; (b) BFS.

Fig. 2. Preparation of the PCs.

In the second phase of production, IP reinforced PC was created. Two different batches containing 5% and 10% IP by total concrete weight were prepared. The IP was first added to the aggregate, resin, and cobalt mixture, which was then mixed for 15 minutes using a mechanical mixer. In the next step, the MEKP was added, and the mixture was blended for an additional 3 minutes. Once homogenization was achieved, the mixture was molded similarly to the PPC and allowed to cure after the molds were removed.

The third production stage involved the creation of the PC mixed with BFS. Again, two different batches were prepared, containing 5% and 10% BFS by total concrete weight. The BFS was initially added to the mixture, followed by 15 minutes of mixing with a mechanical mixer. The MEKP was then added, and the mixture was blended for 3 minutes. After achieving a homogeneous mixture, it was molded in the same manner as the PPC and left to cure after demolding.

In the final stage of production, the PC incorporating both IP and BFS was produced. Two batches were prepared: one with 2.5% IP and 2.5% BFS, and another with 5% IP and 5% BFS by total concrete weight. The IP and BFS were first added to the mixture, followed by 15 minutes of mixing with a mechanical mixer. The hardener was then added, and the mixture was blended for an additional 3 minutes. Once homogenized, the mixture was molded as in the previous stages and allowed to cure after the molds were removed.

2.3. ANN model

Artificial neural networks are capable of learning and processing real-world data in a manner analogous to the human brain. The interconnections between brain cells, or neurons, are represented by mathematical expressions. Among the various connection types, the multilayer perceptron (MLP) is one of the most prominent and widely used structures (Fig. 3). It comprises neurons arranged in layers, with each layer containing a varying number of neurons (Deshpand et al. 2013). Mathematical expressions, that is to say, activation functions, also provide superior solutions to a variety of problems. The weight coefficients in these expressions are identified through the use of diverse regression algorithms, which are referred to as training (Calis et al. 2021). During regression, a range of metrics are employed to evaluate the ANN responses in comparison to the actual results, and the efficacy of the ANN is determined by these metrics.

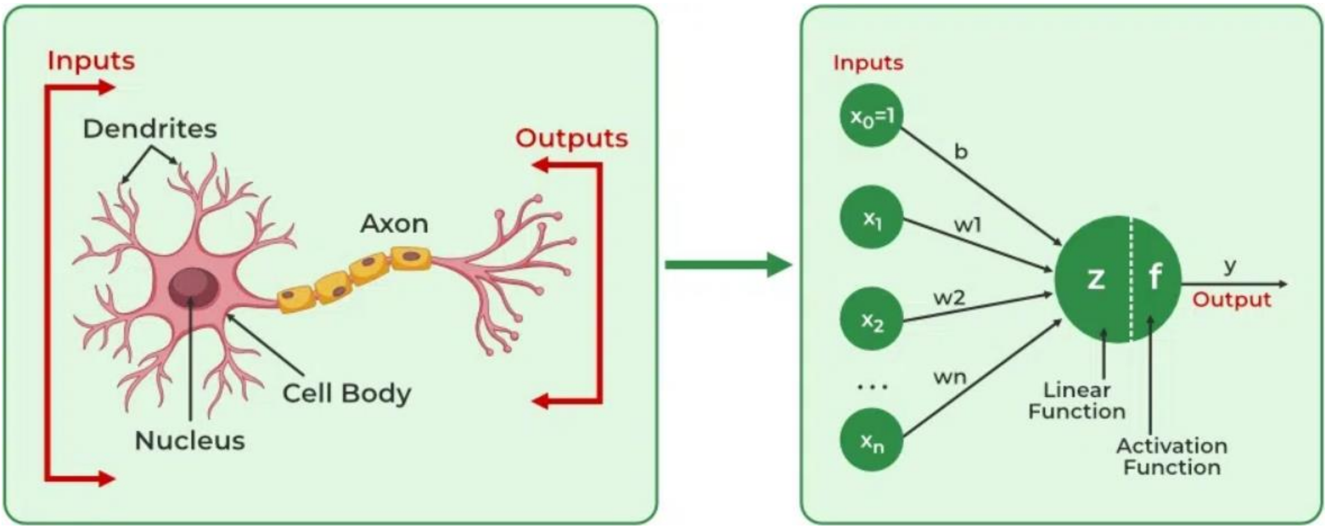

Fig. 3. Biological neurons to artificial neurons (GeeksforGeeks 2024).

In light of the parameters above, it becomes evident that the cluster has a vast array of potential options. Such large-scale problems are referred to as hyperparametric tuning, and various software programs are used to determine the optimal parameters. In this study, the optimal and fastest converging flow was obtained from the combinations of hyperparameters such as the number of neurons, layers, activation functions, learning rate, batch size, epoch, and optimizer.

- Number of neurons: The layers are comprised of activation functions.
- Number of layers: The layers are composed of neurons and linked to each other.
- Activation function: The objective is to ascertain the output of the neuron.
- Learning rate: The step size at each iteration represents the distance between the current point and the minimum of the loss function.
- Batch size: The number of training instances utilized in a specific iteration.
- Epoch: The number of comprehensive runs through the training set.
- Optimizer: This approach allows for the alteration of the neural network's learning rate and weights.

In this paper, the number of neurons is chosen between 2 to 30 per layer, while the number of layers 2 and 3. Activation functions are optimized among softmax, softplus, softsign, relu, tanh, sigmoid, hardsigmoid, linear. While learning rates are prepared for 0.1-0.01-0.001, optimizers are listed among SGD, RMSprop, Adagrad, Adadelta, Adam, Adamax, and Nadam. Epoch and batch size are kept the same during optimizations 100 and 32.

The KerasRegressor module in Python is employed for ANN training, while the GridSearchCV library is utilized for testing all combinations. The entire data set is randomly divided into a training set and a test set in a given ratio. For example, a 70%:30% ratio is selected for the training set and the test set, respectively. The ANN model is trained with the training set and subsequently evaluated on the test data, which it has not previously encountered. The resulting test performance metrics are then obtained. These metrics, namely R^2 (R-squared), MSE (Mean Square Error), and RMSE (Root Mean Square Error) are employed for the assessment of ANN performance. The optimal ANN structure based on optimal hyperparameters with the best error metrics is trained again at 5000 epochs for fine-tuning.

The mathematical definitions of these error metrics are explained as follows:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} \tag{2}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \underline{y}\right)^2}{\sum_{i=1}^{n}\left(y_i - \underline{y}\right)^2} \tag{3}$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value and $\underline{y}$ is the mean of the actual values. A lower MSE value shows the best fit, however, it is significantly influenced by outlier data. RMSE behaves as MSE, also the data is more readily interpretable. An R^2 value approaching 1 indicates that the regression estimates are an exact fit to the data, whereas a value approaching 0 indicates that the model is unable to explain the data.

3. Experimental Studies

The mixtures' density, flexural strength, and compressive strength were evaluated during the experimental studies. The hardened concrete samples were tested for density according to ASTM C642, flexural strength according to ASTM C78/C78M, and compressive strength according to ASTM C109/C109M. The test results for the hardened concrete are summarized in Tables 5–8. These tests were conducted using a 600 kN Form Test machine (Fig. 4) to determine the compressive and flexural strengths of the samples at 7 days.

Table 5. Mechanical properties of the PPCs.

Sample	Density	Flexural fracture load	Flexural strength	Compressive fracture load	Compressive strength	Flexural (max–min)	Compressive (max–min)
	g/cm³	kN	MPa	kN	MPa	MPa	MPa
Plain concrete	2.06	6.89	16.15	116.31	72.69	max: 17.84	max: 77.21
	2.08	6.19	14.51	114.63	71.64	min: 14.51	min: 71.64
	2.13	7.61	17.84	123.53	77.21		

Table 6. Mechanical properties of the IP-reinforced PCs.

Sample		Density	Flexural fracture load	Flexural strength	Compressive fracture load	Compressive strength	Flexural (max–min)	Compressive (max–min)
		g/cm³	kN	MPa	kN	MPa	MPa	MPa
5% IP	Mixture 1	2.12	8.01	18.77	146.79	91.74	max: 21.80	max: 97.84
	Mixture 2	2.23	9.30	21.80	148.61	92.88	min: 18.77	min: 91.74
	Mixture 3	2.17	8.66	20.30	156.55	97.84		
10% IP	Mixture 1	2.19	9.06	21.23	151.65	94.78	max: 22.95	max: 95.54
	Mixture 2	2.21	9.24	21.66	152.86	95.54	min: 21.23	min: 92.91
	Mixture 3	2.21	9.79	22.95	148.66	92.91		

Table 7. Mechanical properties of the BFS-reinforced PCs.

Sample		Density	Flexural fracture load	Flexural strength	Compressive fracture load	Compressive strength	Flexural (max–min)	Compressive (max–min)
		g/cm³	kN	MPa	kN	MPa	MPa	MPa
5% BFS	Mixture 1	2.12	8.50	19.92	140.32	87.70	max: 21.96	max: 88.50
	Mixture 2	2.10	8.67	20.32	141.60	88.50	min: 19.92	min: 87.70
	Mixture 3	2.11	9.37	21.96	140.55	87.84		
10% BFS	Mixture 1	2.08	8.96	21.00	149.94	93.71	max: 22.27	max: 94.43
	Mixture 2	2.08	8.93	20.93	145.22	90.76	min: 20.93	min: 90.76
	Mixture 3	2.08	9.50	22.27	151.09	94.43		

Table 8. Mechanical properties of the IP and BFS-reinforced PCs.

Sample		Density	Flexural fracture load	Flexural strength	Compressive fracture load	Compressive strength	Flexural (max–min)	Compressive (max–min)
		g/cm³	kN	MPa	kN	MPa	MPa	MPa
2.5% IP + 2.5% BFS	Mixture 1	2.12	8.74	20.48	130.98	81.86	max: 20.48	max: 81.86
	Mixture 2	2.03	7.17	16.80	124.58	77.86	min: 16.80	min: 77.86
	Mixture 3	2.02	7.35	17.23	130.16	81.35		
5% IP + 5% BFS	Mixture 1	2.12	8.14	19.08	135.41	84.63	max: 19.73	max: 86.48
	Mixture 2	2.09	8.42	19.73	138.36	86.48	min: 19.08	min: 81.79
	Mixture 3	2.06	8.15	19.10	130.86	81.79		

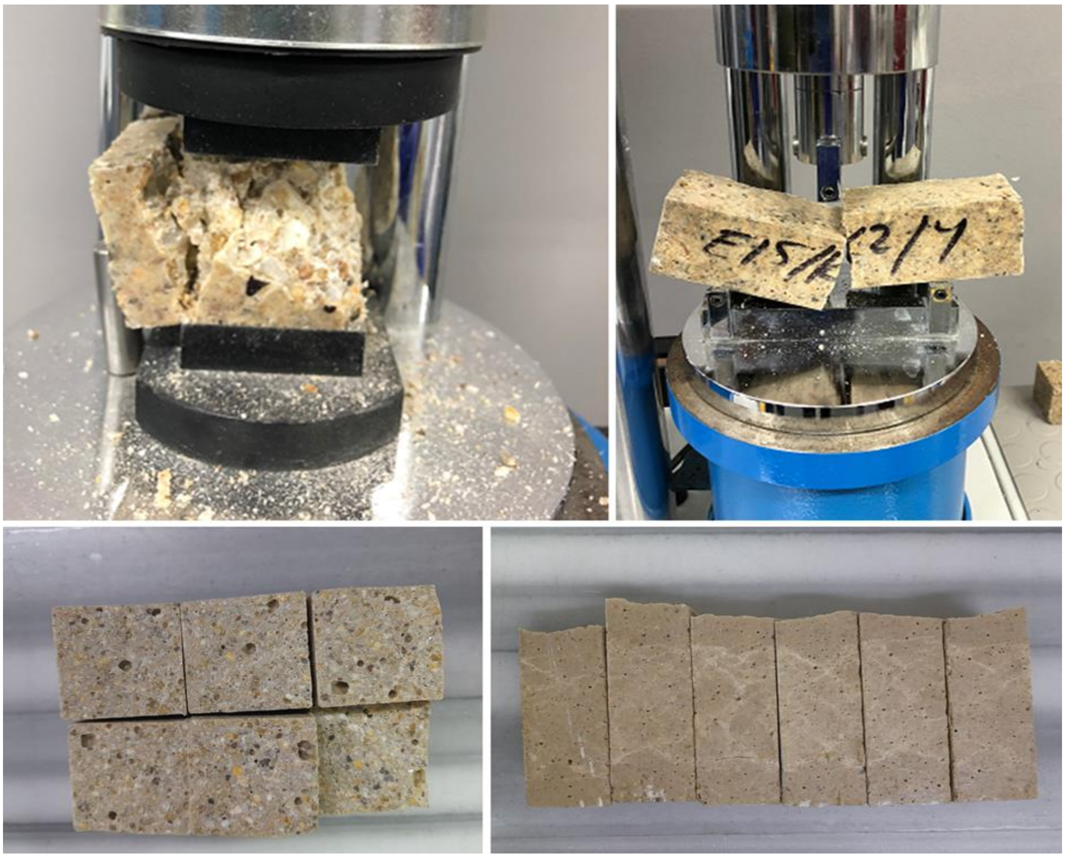

Fig. 4. Mechanical tests on the PCs.

4. Results and Discussion

This section presents a comprehensive analysis of the mechanical properties of Plain Polymer Concretes (PPCs), Iron Powder Polymer Concrete (IPPCs), Blast Furnace Slag Polymer Concrete (BFSPCs), and the combination of IP and BFSPCs, based on the data presented in Tables 5–8. The results are discussed with a focus on density, flexural strength, and compressive strength, highlighting the influence of different reinforcement types and percentages on the performance of the polymer concretes.

The density values for the PPCs, IPPCs, BFSPCs, and IP +BFS PCs are compared to evaluate the effect of different reinforcement types on the overall mass of the concrete. The average densities are summarized in Fig. 5. Given the high density of iron, it can be reasonably assumed that the highest density is observed as 2.21 g/cm^3 at 10% IP.

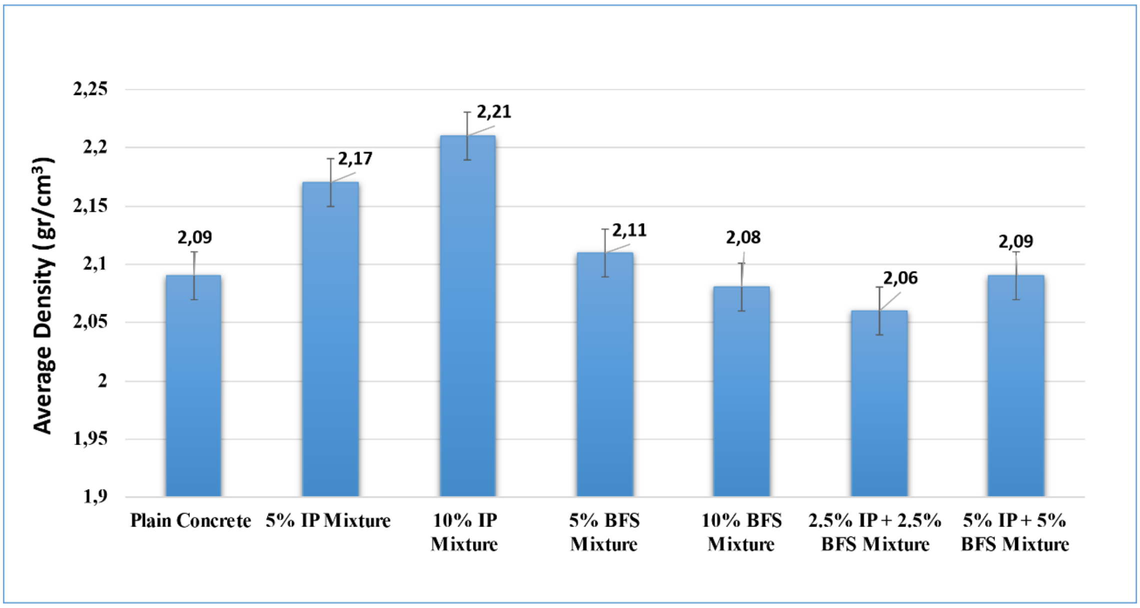

Fig. 5. Average density of the PCs.

To assess the influence of various reinforcement types on the flexural behavior of the components, the flexural strength values of PPCs, IPPCs, BFSPCs, and IP+BFS PCs are compared. The average flexural strength data are summarized in Fig. 6. The results demonstrate that IP and BFS are effective in enhancing the flexural strength of the material when used individually. While the addition of 10% IP and 10% BFS resulted in an increase in tensile strength to 21.95 MPa and 21.40 MPa, respectively, the simultaneous use of both materials led to a reduction in flexural strength.

To assess the influence of various reinforcement types on the flexural behavior of the components, the compressive strength values of PPCs, IPPCs, BFSPCs, and IP+BFS PCs are compared. The average compressive strength values are summarized in Fig. 7. The results of the experiments demonstrated a notable enhancement in the compressive strength of the specimens reinforced with IP, with values exceeding 94 MPa. Similarly, specimens reinforced with 10% BFS also exhibited a high compressive strength of 92 MPa. Nevertheless, the compressive strength of the PCs obtained by combining IP and BFS is found to be below 85 MPa.

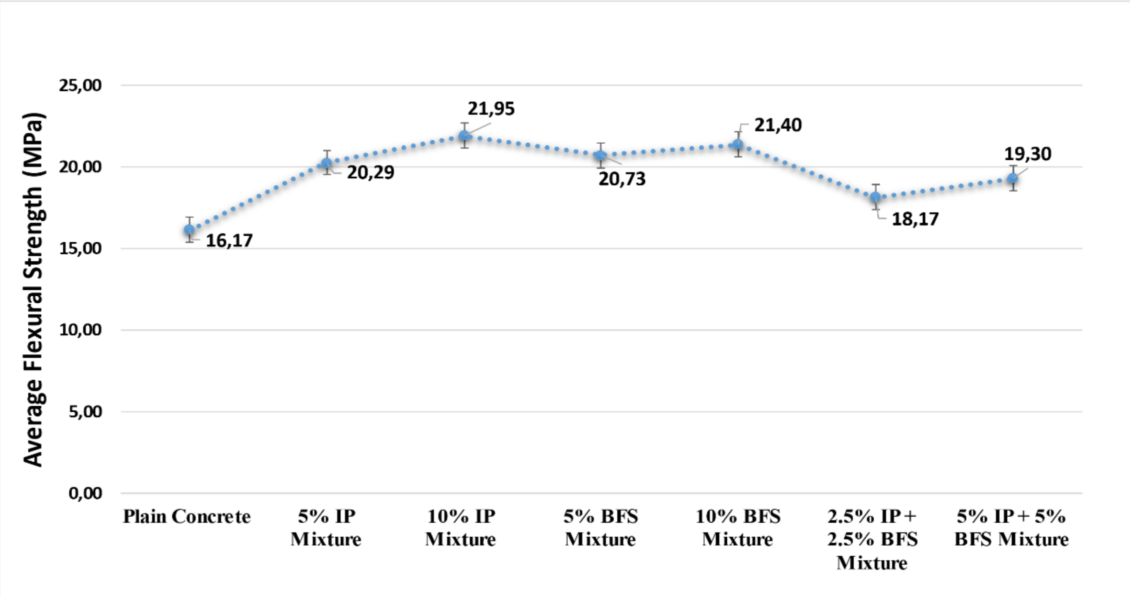

Fig. 6. Average flexural strength of the PCs.

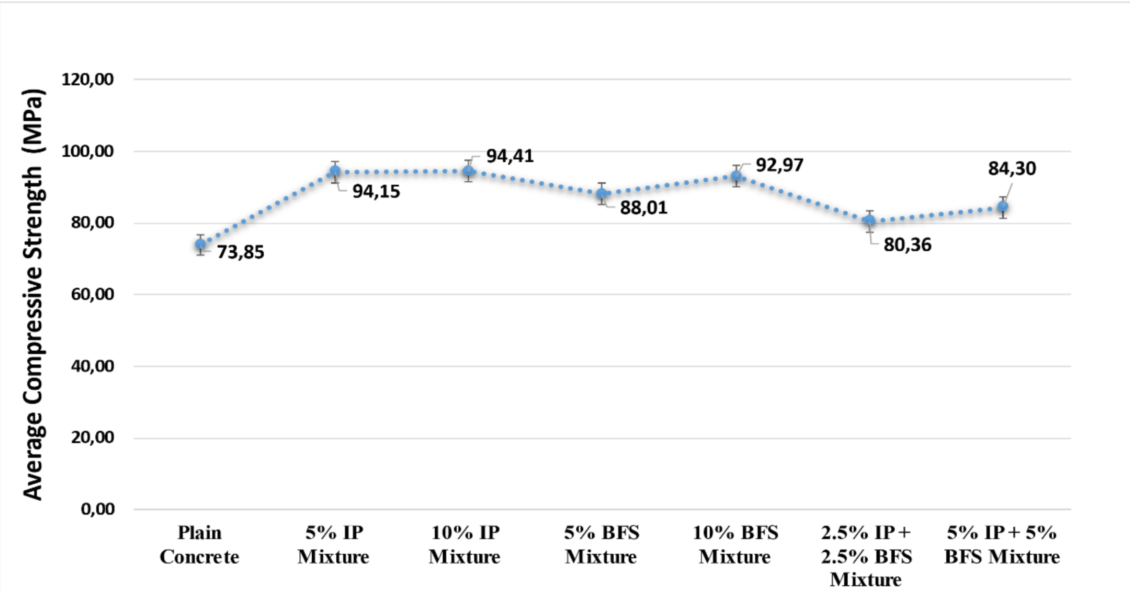

Fig. 7. Average compressive strength of the PCs.

In ANN hyperparameter optimization, the combination of a two-hidden-layer structure, comprising 20 neurons in each layer, SGD optimizer, 0.01 learning rate, and sigmoid function yields the most optimal result with 0.81 MSE that shows model accuracy of ANN structure. The MSE, RMSE, and R^2 error metrics are calculated as 0.007, 0.083, and 0.188 for density, 0.411,0.641, and 0.825 for flexural, and 2.755, 1.660, and 0.947 for compressive, respectively.

The optimal network structure has been calculated and the resulting graphs are presented in Figs. 8–10. The graphs on the left illustrate a comparison between the ANN predictions and the test data set. The greater the degree of aggregation of the data, that is to say, the closer it is to the *Y*=*T* line, the greater the predictor of the model. The graphs in the middle of the figures show the test data set and the ANN predictions, respectively. The graphs on the right demonstrate the percentage error difference between test and predicted data sets. Upon analysis of the three-output data and the error metrics presented above, it can be observed that the most accurate prediction is that of compressive strength, with an error margin of less than 5%. The greatest discrepancy between the predicted and actual values is observed in the case of density, with an error level of 9%.

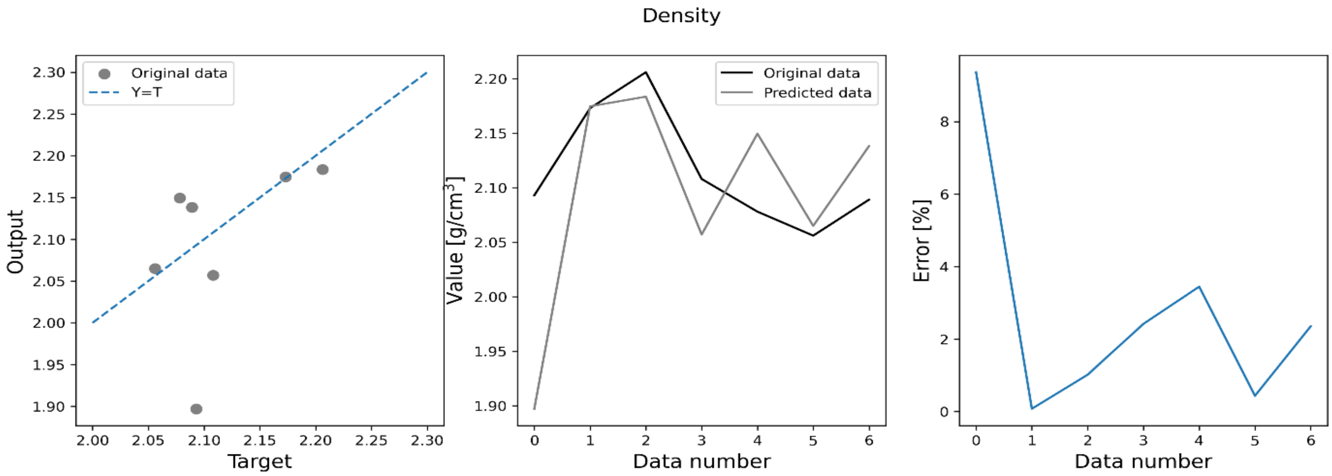

Fig. 8. Comparison of the experimental density data and ANN estimation.

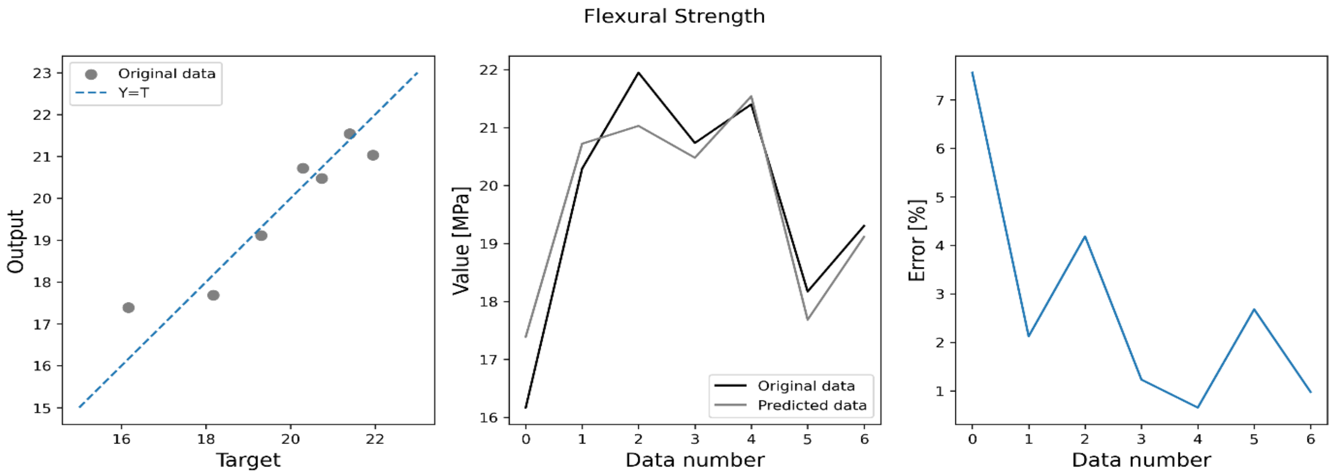

Fig. 9. Comparison of the experimental flexural strength data and ANN estimation.

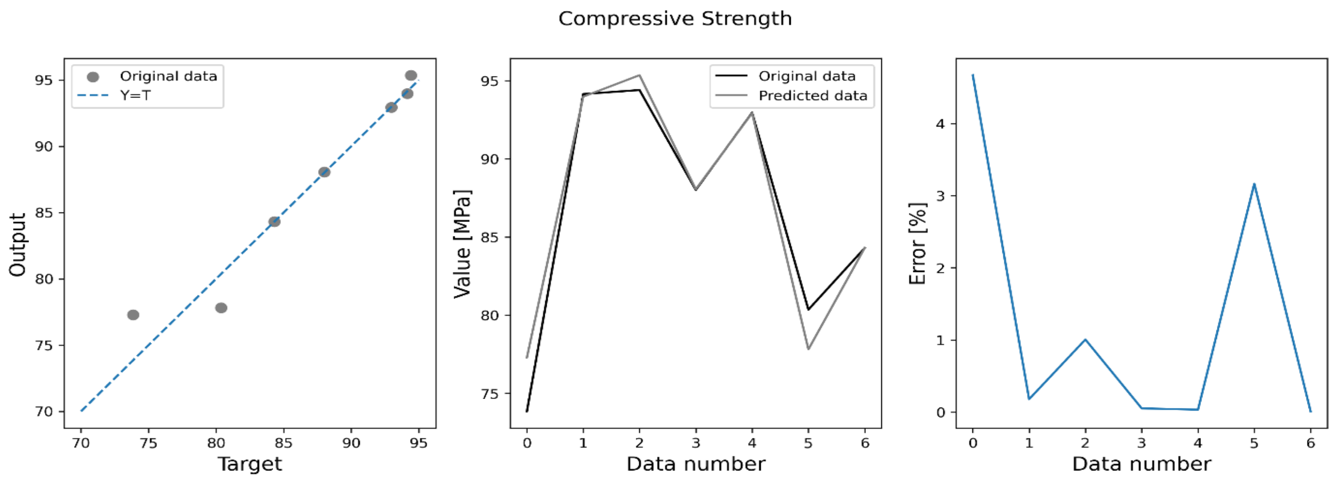

Fig. 10. Comparison of the experimental compressive strength data and ANN estimation.

5. Conclusions

This study investigated the impact of fine materials, specifically iron powder (IP) and blast furnace slag (BFS), on the mechanical properties of polymer concrete (PC). The results demonstrated that the inclusion of these industrial by-products could significantly enhance the mechanical performance of PC, particularly in terms of compressive and flexural strength. Specifically, the addition of 10% IP and 10% BFS individually showed the most notable improvements in both properties, indicating their potential as effective admixtures in PC formulations.

The experimental findings were further supported by the development and application of an artificial neural network (ANN) model, which successfully predicted the mechanical behavior of PC with varying admixture contents. This model proved to be a valuable tool in understanding the complex interactions between the fine materials and the polymer matrix, offering a reliable method for optimizing PC formulations in future studies.

Overall, the integration of IP and BFS into PC not only contributes to enhanced mechanical properties but also promotes the use of industrial by-products in construction materials, aligning with sustainability goals. The insights gained from this study can be applied to the development of high-performance PCs for specialized construction applications, particularly where enhanced strength and durability are required. Future research could explore the long-term durability of these materials in different environmental conditions and expand the scope of fine materials used in PC to further enhance their properties. Additionally, more detailed research can be conducted on the effects of these materials, whose positive contributions to nature and sustainability have been demonstrated in various studies, to enhance these beneficial impacts further.

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Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this manuscript.

Author Contributions

All of the authors made substantial contributions to conception and design, or acquisition of data, or analysis and interpretation of data; were involved in drafting the manuscript or revising it critically for important intellectual content; and gave final approval of the version to be published.

Data Availability

The datasets created and/or analyzed during the current study are not publicly available, but are available from the corresponding author upon reasonable request.

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