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A Field-Based Polynomial Model for Estimating the 28-Day Compressive Strength of Concrete from Slump, Temperature, and Density

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ABSTRACT

Concrete is one of the most widely used materials in the construction industry. Quality control of ready-mixed concrete is important due to the many factors that influence its quality from the production phase to placement and curing. Slump, temperature, density, and compressive strength are commonly used tests for evaluating the quality of concrete. Since the compressive strength test requires 28 days, predicting it using site-specific in situ tests can help engineers assess on-site conditions. To develop a prediction model for compressive strength, 92 samples of ready-mixed concrete were collected in collaboration with the National Standard Organization of Iran in accordance with the relevant national standards. The samples were divided into two groups of training and testing datasets, including 83 and nine randomly selected samples, respectively. According to the proposed model, compressive strength can be predicted from a twelve-term polynomial function in terms of powers of density, slump, and temperature, and their products. The performance of the model was assessed by calculating statistical indicators for the training samples as well as external validation with testing samples not used during model development. The model predicted the 28-day compressive strength with a mean absolute error (MAE) of 0.849 MPa and a coefficient of determination (R^2) of 0.744 for new samples.

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1. Introduction

Ready-mixed concrete is produced in a plastic, fresh, and workable state by the manufacturer under standard conditions, then delivered to the consumer by truck mixers. Evaluating the quality of ready-mixed concrete is challenging, as numerous factors, such as transportation conditions, ambient temperature, and curing methods, can influence its properties from production to placement. Compressive strength is a key factor in determining the quality of ready-mixed concrete that strongly affects the durability and load-bearing capacity of structures. This strength is determined through standard compressive strength tests on concrete specimens. These tests require waiting until the conventional 28-day testing age to obtain the strength. Current standard criteria have some limitations, making the development of alternative evaluation methods necessary [1]. Various parameters can be used to estimate this strength at the time of concrete placement. Some studies focus on pre-production factors to optimize the mix design of concrete. However, studying in situ parameters, such as slump, temperature, and density of fresh concrete, is necessary to control the quality of concrete.

Slump is a widely used test for evaluating the workability of concrete [2]. Recent studies have used machine learning methods to predict concrete properties, including slump [3]. Both the temperature of fresh concrete and the curing temperature significantly influence compressive strength. Since higher temperatures accelerate the hydration process, early strength develops faster, but long-

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term strength is reduced [4-6]. Density is another important parameter that affects compressive strength. In general, denser concretes have higher compressive strength, although the type and gradation of aggregates may alter this relationship [7-9].

However, many existing models predict compressive strength using production-phase characteristics such as the cement-to-water ratio or aggregate type. Based on these characteristics, Nguyen and Phan generated a hybrid adaptive boosting-particle swarm optimization (AB-PSO) model to predict high-performance concrete strength [10]. According to Mahajan and Sharma, aggregate type and cement content can be used in random forest and reduced error pruning tree (REPTree) models to predict compressive strength [11]. Brahmeswari and Rao also utilized machine learning models such as gradient boosting and XGBoost to predict compressive strength using production-stage parameters [12]. Some recent research has utilized fresh concrete test results, particularly slump, in machine learning-based models to improve the accuracy of compressive strength estimation [13]. Reviews of empirical prediction models for high-strength concrete indicate that the majority of these models are based on mix design variables and laboratory testing, rather than on in situ parameter measurements [14]. While some of these methods are effective, developing models that use real-time, in situ parameters of fresh concrete is necessary to support practical decision-making during construction. Predicting concrete strength before 28 days allows an early decision on the need for corrective or remedial actions. While this skill is crucial, only a few research models utilize in situ characteristics for real-time decision-making during construction.

In contrast, the aim of the present study is to fill this gap by developing a comprehensive predictive model using slump, temperature, and density as key parameters measured directly on-site. This model is based on field data from multiple projects across North Khorasan province, Iran. In the development of the model, real-world data from various construction sites were used to make rapid and evidence-based decisions about concrete management. This approach, unlike laboratory-based models, includes the variety of conditions and variability found in the field, making predictions accurate and actionable in real time.

2. Sampling and testing methods

A sampling and testing program was conducted to develop a prediction model for the compressive strength of ready-mixed concrete. For this purpose, 92 samples were collected and tested with the support of the Provincial Standard Offices of North Khorasan. All sampling and testing, including slump, fresh concrete temperature, density, and compressive strength, were conducted following the relevant Iranian National Standards [15-19], which are aligned with the corresponding internationally recognized standards, including ISO, ASTM, EN, and BS EN standards [20-24]. Results from 83 samples were used to develop the rapid prediction model for compressive strength based on slump, temperature, and density. The remaining 9 samples, randomly selected from 92 samples, were used for the final evaluation of the developed model.

Tables 1 and 2 provide the specifications of the 83 samples used for modeling and the 9 samples used for evaluation, respectively. The complete experimental dataset is provided in Table A1 (Appendix A). Tables 1 and 2 display the mean, standard deviation, minimum, maximum, and units for slump, temperature, density, and compressive strength. In the data used for modeling (Table 1), slump ranged from 45 to 140 mm, temperature from 7 to 32°C, density from 2037 to 2430 kg/m³, and compressive strength from 19.6 to 31.5 MPa. These tables show that the samples cover a wide range of different conditions well, which helps to investigate the effect of different variables on the compressive strength of concrete more comprehensively and accurately. Fig. 1 presents the histograms of the variables used in the model. Data normality was examined using the Jarque–Bera, Lilliefors, and Kolmogorov–Smirnov tests at $\alpha = 0.05$ [25]. Based on these tests, compressive strength values approximately followed a normal distribution, slump and density showed non-normal behavior, and temperature showed mixed results across the tests. Slump and density are operational field variables, and temperature is affected by local environmental conditions. Therefore, some departure from normality in the raw input variables of slump and density is practically understandable in field-based concrete data. A key strength of this dataset is that it comes from various construction projects in the North Khorasan province using standardized sampling and testing procedures. The model can accurately represent field conditions because it was developed based on field data rather than laboratory or simulated data.

Table 1. Data specifications of 83 samples used for developing the prediction model.

Parameters	Abbreviation	Type	Mean	Standard Deviation	Minimum	Maximum	Unit
Slump	S	Input	83	21	45	140	mm
Temperature	T	Input	24	7	7	32	℃
Density	D	Input	2296	79	2037	2430	Kg/m³
Compressive strength	P	Output	26.4	2.7	19.6	31.5	MPa

Table 2 .Data specifications of 9 samples used for evaluating the prediction model.

Parameters	Abbreviation	Type	Mean	Standard Deviation	Minimum	Maximum	Unit
Slump	S	Input	79	11	65	90	mm
Temperature	T	Input	22	8	10	32	℃
Density	D	Input	2341	52	2233	2390	Kg/m³
Compressive strength	P	Output	27.4	2.7	23.3	30.4	MPa

3. Development of the prediction model

Slump, temperature, and density are the input variables for the compressive strength prediction model. To identify an appropriate form of the prediction model, the correlation between concrete compressive strength (as the output) and different functional forms of the input variables was examined, including exponential, logarithmic, radical, trigonometric, and power functions.

An initial analysis of the results indicates that the highest correlation coefficient with compressive strength exists for first-, second-, and third-order power terms, as well as selected products and ratios of input variables, as summarized in Table 3. The corresponding p-values are also reported in Table 3, and most of the correlations are statistically significant at $p < 0.05$. However, a few combinations, such as $D/(S \cdot T)$ and $1/T$, are not statistically significant and were therefore not considered in the final model. Based on these results, all effective parameters were included in developing a polynomial regression model for predicting the compressive strength of concrete. The influence of each term was examined during the regression process, and terms with negligible effects on prediction accuracy were removed. The final model, obtained by the least squares method, is shown in Eq. 1. In this equation, the compressive strength is expressed as a polynomial function of slump (S), temperature (T), and density (D):

$$F_c' = a_1 + a_2S + a_3S^2 + a_4S^3 + a_5T + a_6T^2 + a_7T^3 + a_8D + a_9S.D + a_{10}T.D + a_{11}S.T + a_{12}S.T.D \tag{1}$$

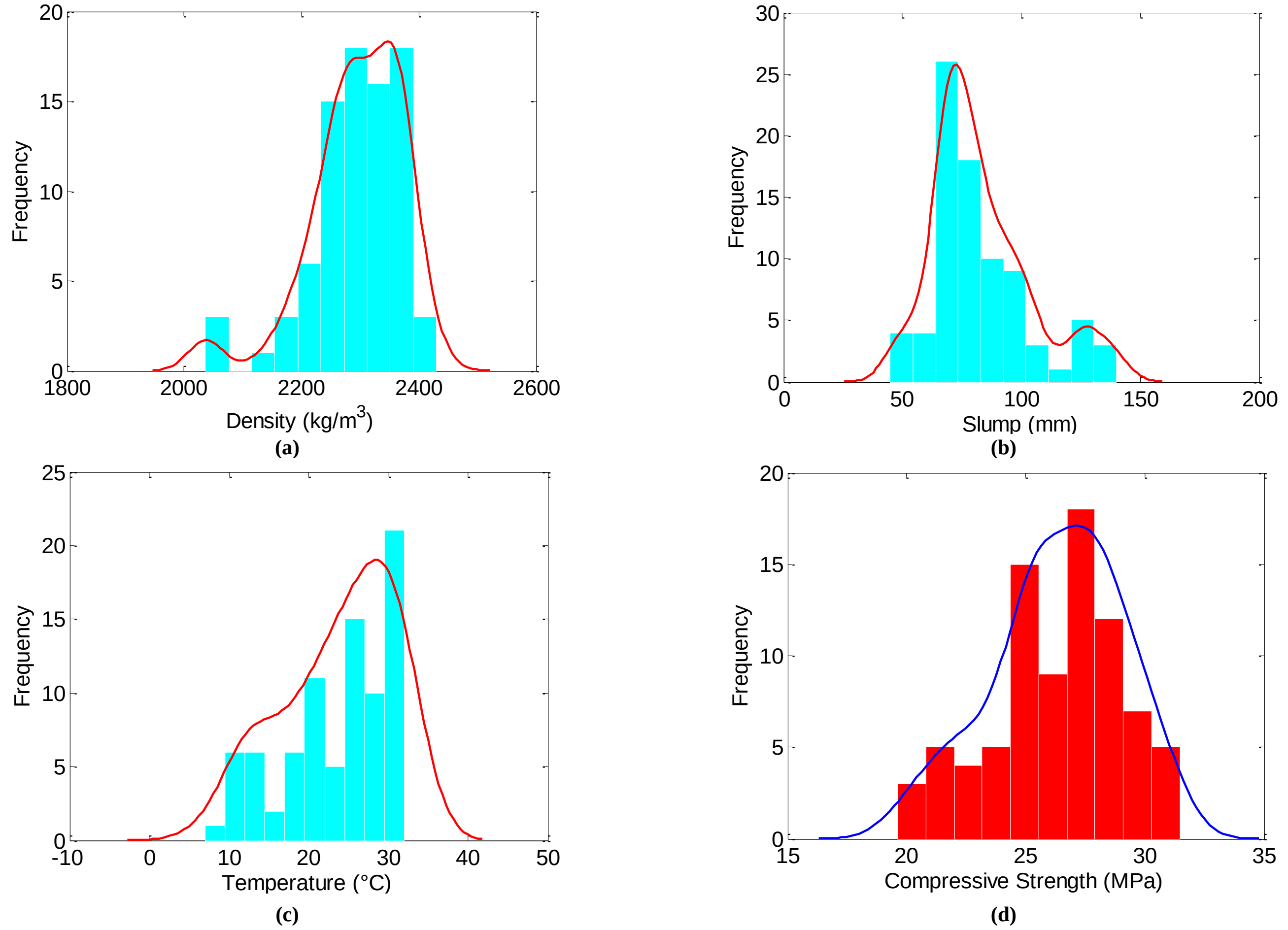

Fig. 1. Normal distribution of the data: (a) Density (kg/m³), (b) Slump (mm), (c) Temperature (°C), (d) Compressive strength (MPa).

Table 3. Correlation coefficients between different forms of input variables and concrete compressive strength.

Parameters	S	T	D	S^2	T^2	D^2	S^3	T^3	D^3
Correlation coefficient	-0.357	-0.303	0.227	-0.419	-0.354	0.223	-0.468	-0.391	0.219
P-value	0.004	0.003	0.028	0.003	0.004	0.031	0.002	0.009	0.034
Parameters	**S.T**	**S.D**	**T.D**	**S.D.T**	**1/S**	**1/T**	**1/D**	**S/(T.D)**	**D/(S.T)**
Correlation coefficient	-0.468	-0.334	-0.274	-0.455	0.217	0.157	-0.230	-0.481	-0.029
P-value	0.002	0.001	0.008	0.004	0.036	0.131	0.023	0.009	0.784

Fig. 2 shows a diagram of the overall modeling procedure. This includes preparing the database, selecting the input and output parameters, dividing the data into training and testing sets, conducting the regression process, and evaluating the model. This diagram provides a visual summary of the main steps from the raw data to the final prediction model.

In Eq. 1, F_c' is the compressive strength in MPa, and the coefficients a_1 to a_{12} are the unknown coefficients of the model. All parameters for the data samples are set in the form of a matrix according to Eq. 2:

$$[F_c'] = [1 \quad S \quad S^2 \quad S^3 \quad T \quad T^2 \quad T^3 \quad D \quad S.D \quad T.D \quad S.T \quad S.D.T\,] \begin{bmatrix} a_1 \\ \vdots \\ \cdot \\ a_{12} \end{bmatrix} \tag{2}$$

According to the least squares method, the vector of unknown coefficients (*X*) can be calculated from Eq. 3:

$$y_{n\times 1} = A_{n\times 12}X_{12\times 1} \Rightarrow X = (A^TA)^{-1}A^Ty \tag{3}$$

Then the residual vector can be obtained from Eq. 4:

$$e = y - AX \tag{4}$$

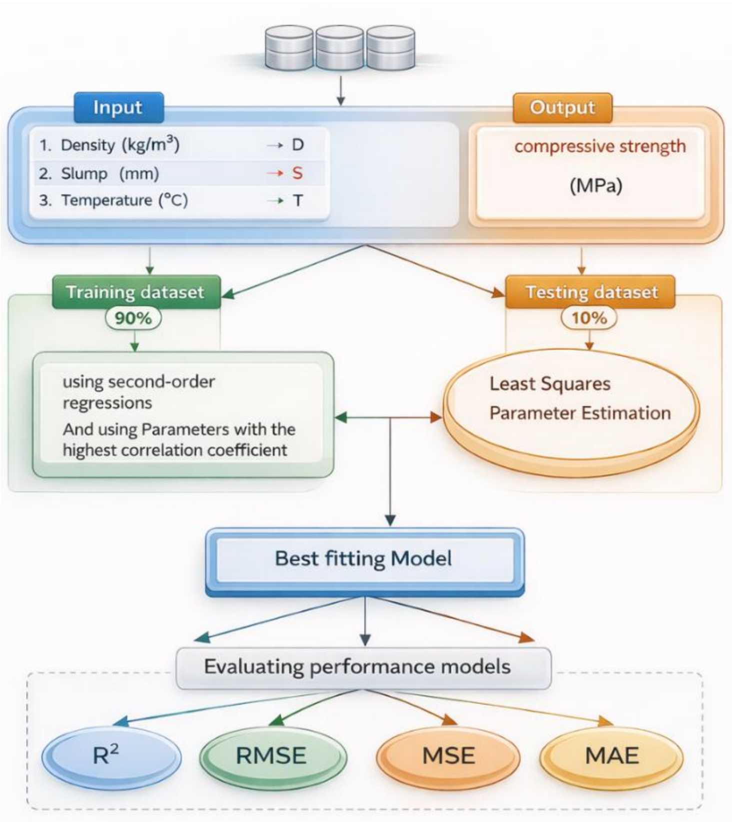

Fig. 2. Schematic overview of the modeling process, from data preparation and input and output parameter selection to regression analysis and model evaluation.

If a singularity occurred in the inverse matrix of Eq. 3, Tikhonov's method of regularization was used to solve it. A secondary factor variance test was used to ensure error adjustment and correct estimation of coefficients. The test is based on the chi-square distribution at a 95% confidence level [26] and was applied in this study as Eq. 5:

$$\frac{\sigma_0^2\chi^2_{df,\frac{\alpha}{2}}}{df} < \hat{\sigma}_0^2 < \frac{\sigma_0^2\chi^2_{df,1-\frac{\alpha}{2}}}{df} \tag{5}$$

In this equation, σ_0^2 is the estimated variance factor, *df* is the degree of freedom (equal to the number of observations minus 12 unknown coefficients), and α *is* the significance level (Type I error). This inequality gives the confidence interval for the variance. Also, to evaluate the stability of the coefficients of each model, the intentional error method was applied to each coefficient to test the residuals on the estimated observations through error simulation [27].

Table 4 presents the coefficients, their standard deviations, and corresponding p-values of the twelve-term prediction model. Most coefficients are statistically significant, and their small standard deviations indicate precise estimation. Although the ninth coefficient (slump × density) is not individually statistically significant, it was retained for structural and predictive reasons. Because of the limited sample size and the resulting ill-conditioning (near-singularity) of the design matrix associated with the model structure, the coefficient estimates may become unstable. Therefore, the p-value of this term was not used as the sole criterion for exclusion. Since the model includes the three-way interaction term (slump × temperature × density), retaining the slump × density term preserves the hierarchical structure of the polynomial model. In addition, this term showed a non-negligible negative correlation with compressive strength relative to the other transformed input variables (Table 3), and its removal increased the overall mean squared error by 0.469%, indicating a slight reduction in predictive accuracy.

Table 4. Coefficients and standard deviations of the compressive strength prediction model.

Coefficients	Values	Standard deviation	P-Value
a_1	-0.01223751	0.005117	0.0194
a_2	-0.58810606	0.246722	0.0198
a_3	0.00852123	0.002610	0.0016
a_4	-0.00003820	0.000009	0.0000
a_5	-0.11111143	0.046205	0.0187
a_6	-0.08002689	0.029171	0.0076
a_7	0.00093905	0.000456	0.0433
a_8	0.01114784	0.003672	0.0033
a_9	0.00000556	0.000089	0.9505
a_{10}	0.00090258	0.000255	0.0007
a_{11}	0.02373212	0.010056	0.0210
a_{12}	-0.00001050	0.000004	0.0171

4. Evaluating the efficiency of the proposed model

The efficiency of the proposed model and its prediction accuracy were evaluated in two stages. First, the internal performance of the model was assessed by calculating statistical indicators. Second, external validation was carried out using data not employed during model development.

To evaluate the error via statistical indicators, the residuals of the model are provided in Fig. 3. In this figure, the residual values are presented to display both the general trend and the variations corresponding to each of the samples. The residuals are small and mostly distributed symmetrically around zero, showing that the model's predictions are generally reliable and free from systematic bias. In addition, other indicators were calculated to better assess the accuracy of the predictions. The considered indicators include mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), the coefficient of determination (R^2), and the minimum and maximum prediction errors (differences between the predicted and observed values). Table 5 presents the evaluation results for both training and test datasets. The p-values of the coefficients are reported in Section 3, where they are shown to be statistically significant and within acceptable ranges. Therefore, they are not discussed further in this section.

The mean absolute error (MAE) for the training dataset was 1.237 MPa, roughly 4.7% of the average compressive strength, reflecting the average size of the prediction errors. The mean squared error (MSE) reached 2.155 MPa^2, while the residual variance, adjusted for degrees of freedom, was 1.578 MPa^2. Both values are low compared with the variability in compressive strength, indicating that the average prediction errors are relatively small. The coefficient of determination (R^2) was 0.699, showing that 69.9% of the variation in the observed data is captured by the model, while 30.1% remains unexplained. This conclusion is also supported by the comparison graph (Fig. 4), where the fitted line is close to the ideal y = x line, and most points lie near it.

To evaluate the external performance of the model, nine data points that were randomly set aside at the beginning and not used during model training were employed. The MAE and RMSE for the nine testing samples are 0.849 MPa and 1.285 MPa, respectively. These values are slightly lower than the corresponding values for the training dataset. This observation indicates that the model can effectively predict the unseen data. The coefficient of determination, $R^2 = 0.744$, confirms that the model can capture a substantial proportion of the variance. Furthermore, the minimum and maximum prediction errors are -3.48 MPa and 0.89 MPa, respectively. These values show limited variation and are smaller than those observed for the training data. A closer look at the residuals indicates that the model can predict samples with compressive strengths below 25 MPa more accurately. Since such low early-age strengths are undesirable, the model's ability to estimate the 28-day compressive strength from initial measurements (slump, density, and temperature) can help guide decisions on-site.

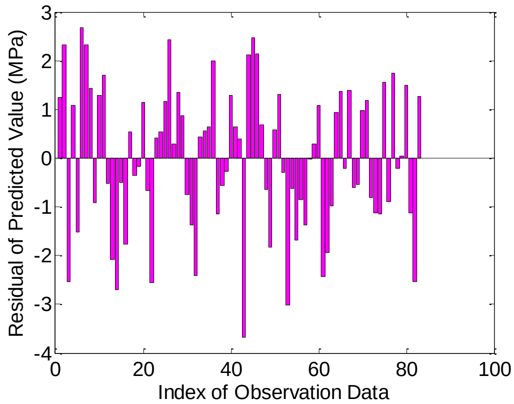

Fig. 3. Residuals of model predictions for all samples.

The main objective of this model is to offer a fast and simple method for estimating compressive strength based on basic slump, temperature, and density tests. Thus, the observed errors mainly reflect natural variations in concrete quality and uncertainties in production, transportation, and placement. Considering these, the proposed model can be used as a useful and efficient tool for rapid and practical prediction of the compressive strength of ready-mixed concrete in real conditions and on-site projects. It should be mentioned that this model is applicable to the range of input parameters considered in this study. According to Table 1 and considering the accuracy of the prediction model, the recommended ranges for input parameters are 50 to 140 mm, 7°C to 32°C, and 2040 to 2430 kg/m^3 for slump, temperature, and density, respectively. At the same time, one limitation of this study is the relatively small number of training and testing samples. This was mainly due to the need to use only sufficiently reliable and well-documented data for modeling and validation. Therefore, a smaller but more reliable dataset was preferred. Future work should validate the model using larger independent datasets when such reliable data become available.

Table 5. Model performance metrics for the training and testing datasets (MAE, MSE, RMSE in MPa; R^2 unitless).

Dataset	MAE	MSE	RMSE	R^2	Min Error	Max Error
Training dataset	1.237	2.155	1.468	0.699	-3.68	2.67
Testing dataset	0.849	1.651	1.285	0.744	-3.48	0.89

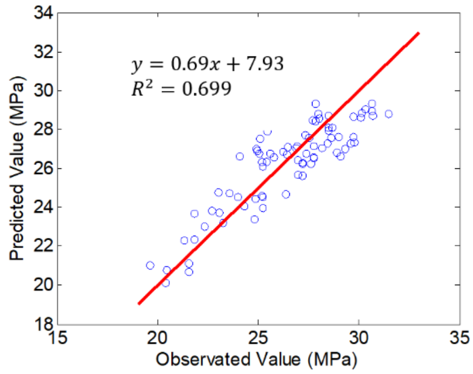

Fig. 4. Comparison of observed and predicted compressive strength values.

5. Effects of temperature, density, and slump on the compressive strength of ready-mixed concrete

After developing the prediction model, the influence of key input parameters on compressive strength is considered. In this section, the effects of temperature, density, and slump on the compressive strength of ready-mixed concrete are analyzed using the proposed model. Fig. 5 provides a clearer analysis of how variations in temperature, density, and slump affect compressive strength. To illustrate parameter interactions, graphs were created by varying two parameters along the axes while holding the third constant. Based on the adopted approach, the following parameter values were chosen for constructing the interaction graphs: Density: 2000, and 2400 kg/m³, Slump: 40 and 120 mm, and Temperature: 15 and 35°C.

5.1. Effect of temperature and slump on compressive strength

The contour plots in Figs. 5a and 5b show an approximately circular region in the temperature–slump space where the predicted compressive strength reaches its highest values. For both densities of 2000 and 2400 kg/m³, the peak region is observed around slump values near 91–103 mm and temperatures approximately 14–21°C. Moving away from this region in either direction, whether by increasing or decreasing the slump or by changing the temperature, is associated with a gradual reduction in predicted strength. For example, at a density of 2000 kg/m³, increasing slump to 140 mm at 15°C corresponds to a decrease in predicted strength from 26.6 MPa down to 20.7 MPa. A similar trend is seen at 2400 kg/m³, where predicted strength decreases from near 30.4 MPa to 21.4 MPa under comparable conditions. Likewise, fixing slumps and increasing temperatures tend to reduce predicted strength. After observing the patterns in Figs. 5a and 5b, the optimal ranges for slump and temperature were calculated using the prediction model across the studied density interval (2000-2450 kg/m³). The optimal ranges for slump and temperature that lead to maximum compressive strength are found to be 89–105 mm and 17–18°C, respectively. The optimum temperature range is close to the standard curing temperature of 20 ± 2 °C used in the Iranian and European standards and is also consistent with ASTM practice and previous studies [5, 19, 23, 28].

It is recognized that workability (as indicated by slump) and temperature affect hydration and compaction, and as a result, influence compressive strength. While earlier studies such as Neville emphasize the influence of mixture proportions and curing on strength, they do not prescribe a single optimum for slump and temperature under all conditions [6]. Our results similarly show a peak region in the parameter space where predicted compressive strength is highest.

5.2. Effect of density and temperature on compressive strength

Figs. 5c and 5d show the effects of density and temperature on compressive strength at two fixed slump levels, 40 mm and 120 mm, respectively. As can be seen in these figures, increasing density leads to higher compressive strength. For example, at a slump of 40 mm and within the temperature range of 14–21°C, raising density from 2000 to 2400 kg/m³ increases the predicted strength from about 22.5 MPa to roughly 30.3 MPa, a 35% increase. At the higher slump of 120 mm, the same amount of change in density results in a smaller increase of about 8%, from around 25.7 MPa to 27.8 MPa. This indicates that the influence of density on compressive strength is more evident at lower slump levels.

As observed in Figs. 5a and 5b, the effect of temperature follows a similar trend, with an optimal range identified between 14 and 21°C. Moving outside this range reduces the predicted strength. Unlike the slump–temperature plots, there is no distinct optimal density, and higher density consistently improves strength. This conclusion is consistent with the finding of other research, such as that of Mehta and Monteiro, that concrete density significantly affects compressive strength [7]. These observations highlight that both density and temperature are important parameters, while the magnitude of density effects depends on the slump level.

The effect of temperature on strength reduction is investigated at a representative density of 2400 kg/m³. At this density, the maximum compressive strength of 30.37 MPa occurs at a slump of 92 mm and a temperature of 17°C, according to Eq. 1. Keeping slump and density constant, increasing the temperature to 32°C reduces the predicted strength by 11.2% to 26.98 MPa. Decreasing the temperature to 7°C reduces the strength by 17.8%, resulting in a new value of 24.96 MPa. These results show how deviations from the optimal temperature range can reduce the compressive strength.

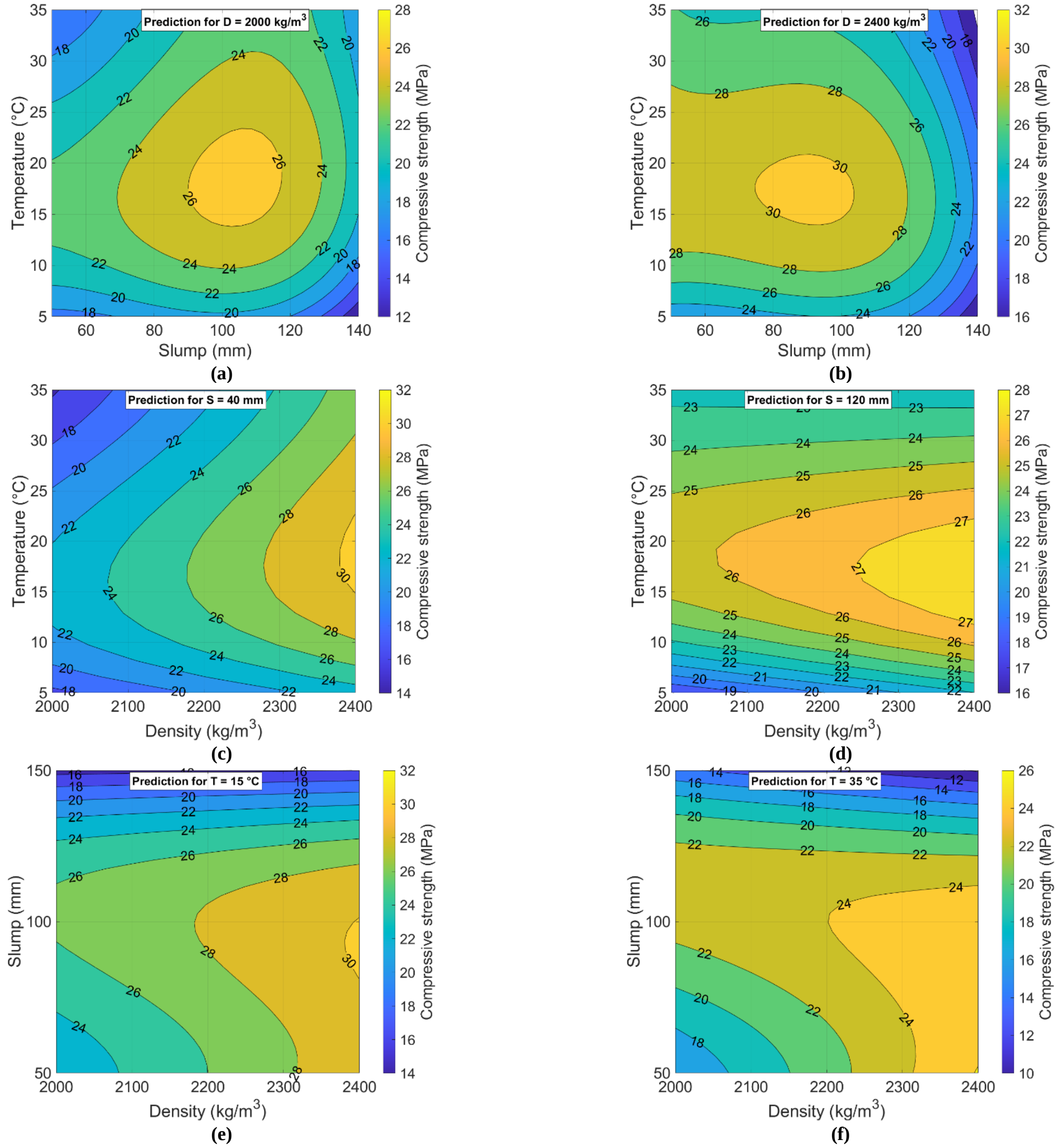

Fig. 5. Effect of key parameters on the 28-day compressive strength of ready-mixed concrete: (a and b) density fixed at 2000 and 2400 kg/m³, (c and d) slump fixed at 40 and 120 mm, and (e and f) temperature fixed at 15 and 35 °C.

5.3. Effect of density and slump on compressive strength

Figs. 5e and 5f show the combined effect of density and slump on compressive strength at fixed temperatures of 15°C and 35°C, respectively. The general shape of these plots is similar to that observed in Figs. 5c and 5d. In contrast to Figs. 5a and 5b, no distinct optimum region is observed for slump and density. Instead, compressive strength consistently increases with an increase in density in both figures. For example, at a slump of about 100 mm, increasing density from 2000 to 2400 kg/m³ raises the compressive strength from approximately 26.3 MPa to about 30 MPa at 15°C and from around 22.7 MPa to nearly 25.3 MPa at 35°C. At the same time, the influence of slump follows a pattern similar to that of Figs. 5a and 5b. Slump values in the range of approximately

90–100 mm lead to higher compressive strength, and deviations from this range reduce the strength. These results confirm that an intermediate slump range remains favorable across different temperature conditions.

Similar to section 5.2, the effect of slump is investigated at a representative density of 2400 kg/m³. Increasing slump to 140 mm from the optimum value of 92 mm at a constant density and temperature of 2400 kg/m^3 and 17 °C reduces the compressive strength by 30.3% to 21.4 MPa. Conversely, decreasing slump to 50 mm reduces the compressive strength by 3.2%. These results show that increasing slump is more effective in reducing the compressive strength, and the effect of reducing the slump is negligible. The asymmetry in the predicted effect of slump is seen across the studied slump range in Fig. 5(a) and Fig. 5(b), not only at the extreme values. Therefore, it is not interpreted as a boundary effect of the model and may be explained as follows. At high slump, strength decreases due to an increase in the water-cement ratio. In contrast, at low slump, the mix becomes less workable and harder to compact, but the lower water-cement ratio partly balances this effect.

6. Conclusion

In this study, a prediction model was developed for the 28-day compressive strength of concrete based on density, slump, and temperature of fresh concrete. Non-time-consuming tests can be used to predict the results of time-dependent compressive strength tests, enabling engineers to make quick decisions about concrete quality control. For this purpose, 92 ready-mixed concrete samples were tested from real projects in North Khorasan province. Using real samples instead of laboratory ones increases the validity and reliability of the model for use in the construction industry. Results from 83 samples were used to develop the rapid prediction model for compressive strength, while the remaining randomly selected 9 samples were used for the final evaluation of the developed model.

- A prediction model consisting of twelve terms was developed to estimate the compressive strength of concrete based on slump, temperature, and density. For this purpose, different combinations and functional forms of these variables were examined. The model includes a constant term, polynomial terms up to the third order for slump and temperature, a linear density term, and product terms of slump–density, temperature–density, slump–temperature, and the product of these three variables. The prediction model is applicable to the considered range of input parameters, 50 to 140 mm, 7°C to 32°C, and 2040 to 2430 kg/m^3 for slump, density, and temperature, respectively.
- The performance of the proposed model was evaluated for both training and testing datasets. Statistical indicators included p-values of the coefficients, mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), coefficient of determination (R^2), and maximum and minimum prediction errors. In all cases, the model predicted the results with good accuracy. It is notable that the performance of the model on the testing data was close to and slightly better than the training data. This evidence shows that this model can estimate the compressive strength in terms of density, slump, and temperature for new samples.
- It was found that the optimal ranges for slump and temperature across all studied densities leading to maximum compressive strength are 89–105 mm and 17–18°C, respectively.
- In contrast to slump and temperature, density does not have a specific optimum range, and increasing density increases the compressive strength.
- The prediction model demonstrates that the optimum values for slump and temperature at a density of 2400 kg/m³ are 92 mm and 17°C. At these conditions, the compressive strength reaches 30.37 MPa. Keeping density and slump constant and increasing the temperature to 32°C reduces the strength by 11.2%, while decreasing it to 7°C causes a 17.8% reduction. These findings indicate that the impact of temperature deviations on compressive strength is significant.
- In a similar manner, keeping density and temperature constant and increasing the slump to 140 mm reduces the strength by 30.3%, whereas decreasing slump to 50 mm reduces it by only 3.2%. These results show that the effect of increasing slump on compressive strength is considerable, while the effect of reducing the slump is negligible.

Statements & Declarations

Author contributions

Aliakbar Yahyaabadi: Conceptualization, Supervision, Methodology, Validation, Formal analysis, Writing – Original Draft, Writing – Review & Editing.

Seyyed Ghasem Rostami: Methodology, Formal analysis, Modelling.

Masood Mohammadi: Data collection, Performing experimental tests.

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Declarations

The authors declare no conflict of interest.

Data availability

The data presented in this study are available in the article.

Appendix — Supplementary Experimental Data

Table A1. Experimental results of 92 concrete samples used for model development (slump, temperature, density, and 28-day compressive strength).

No.	Slump (mm)	Temperature (℃)	Density (kg/m^3)	Compressive strength (MPa)	No.	Slump (mm)	Temperature (℃)	Density (kg/m^3)	Compressive strength (MPa)
1	70	22	2212	27.8	47	95	12	2390	25.4
2	80	26	2283	29.3	48	90	28	2292	28.9
3	75	27	2297	24.1	49	95	29	2300	29.1
4	70	25	2402	29.8	50	100	26	2308	29.8
5	100	18	2303	27.8	51	90	7	2265	25.2
6	100	18	2243	31.5	52	70	10	2360	26.5
7	90	26	2272	29.6	53	70	32	2233	21.8
8	120	32	2192	24.8	54	45	13	2137	25.2
9	110	27	2244	25.4	55	85	22	2338	30.3
10	70	30	2314	27.0	56	90	17	2390	30.2
11	80	21	2330	30.7	57	130	32	2365	20.5
12	80	18	2273	28.1	58	70	25	2380	25.5
13	100	25	2188	24.9	59	75	25	2039	23.1
14	100	18	2196	25.7	60	70	30	2380	25.1
15	125	32	2310	21.8	61	50	22	2370	28.0
16	90	24	2233	26.9	62	60	25	2380	26.8
17	70	27	2197	23.0	63	70	28	2390	27.5
18	70	15	2282	28.5	64	135	29	2360	20.4
19	100	12	2238	27.3	65	70	27	2370	28.6
20	70	13	2252	26.9	66	70	29	2350	25.9
21	70	12	2276	28.2	67	90	29	2430	25.5
22	125	30	2350	22.3	68	90	30	2350	25.0
23	80	18	2266	25.9	69	125	32	2350	21.3
24	80	13	2288	28.5	70	100	31	2360	27.2
25	70	30	2360	27.0	71	80	31	2350	27.6
26	80	32	2280	24.2	72	80	25	2268	26.9
27	110	25	2303	28.5	73	90	13	2207	29.0
28	65	22	2281	29.8	74	90	27	2263	26.3
29	75	32	2236	24.3	75	70	23	2350	27.9
30	75	20	2360	30.7	76	70	31	2350	26.4
31	140	22	2360	21.5	77	80	31	2350	27.2
32	80	12	2350	27.7	78	70	30	2370	27.8
33	130	32	2280	19.6	79	70	29	2350	25.8
34	60	23	2314	25.1	80	70	32	2390	25.2
35	140	14	2370	21.5	81	70	29	2360	25.6
36	65	10	2350	23.3	82	70	32	2350	27.2
37	80	18	2236	28.7	83	80	29	2290	25.2
38	105	26	2266	27.8	84	50	32	2310	26.4
39	90	22	2300	30.7	85	80	22	2325	28.5
40	80	32	2263	23.6	86	90	18	2380	30.4
41	50	32	2304	24.0	87	55	14	2037	23.2
42	85	23	2164	26.4	88	70	12	2410	30.1
43	70	32	2250	25.2	89	65	20	2037	22.7
44	70	27	2320	27.4	90	80	20	2264	25.7
45	60	28	2233	24.9	91	65	16	2350	30.1
46	90	13	2390	30.0	92	65	22	2350	29.4

References

[1] Skrzypczak, I., Kokoszka, W., Zięba, J., Leśniak, A., Bajno, D., Bednarz, L. A Proposal of a Method for Ready-Mixed Concrete Quality Assessment Based on Statistical-Fuzzy Approach. Materials, 2020; 13: 5674. doi:10.3390/ma13245674.

[2] Tattersall, G. H., Banfill, P. The rheology of fresh concrete. 1st ed. London (UK): Pitman Publishing 1983.

[3] Wang, Z., Sun, T., Sun, Y., Liu, N. Evaluating the strength properties of high-performance concrete in the form of ensemble and hybrid models using deep learning techniques. Scientific Reports, 2025; 15: 25453. doi:10.1038/s41598-025-10860-y.

[4] Mahboub, K. C., Cutshaw, Q. A. Effects of Fresh Concrete Temperature and Mixing Time on Compressive Strength of Concrete. ACI Materials Journal, 98: doi:10.14359/10161.

[5] Kaleta-Jurowska, A., Jurowski, K. The Influence of Ambient Temperature on High Performance Concrete Properties. Materials, 2020; 13: 4646. doi:10.3390/ma13204646.

[6] Neville, A. M. Properties of concrete. 4th ed. Longman; 1995.

[7] P.K. Mehta, P. J. M. Concrete: Microstructure, properties, and materials. 3rd ed. Columbus (OH): McGraw-Hill; 2006.

[8] Iffat, S. Relation Between Density and Compressive Strength of Hardened Concrete. Challenge Journal of Concrete Research Letters; Vol 6, No 4 (2015), 2017; doi:10.20528/cjcrl.

[9] Sánchez-Mendieta, C., Galán-Díaz, J. J., Martinez-Lage, I. Relationships between density, porosity, compressive strength and permeability in porous concretes: Optimization of properties through control of the water-cement ratio and aggregate type. Journal of Building Engineering, 2024; 97: 110858. doi:10.1016/j.jobe.2024.110858.

[10] Nguyen, D.-L., Phan, T.-D. Enhanced prediction of compressive strength in high-strength concrete using a hybrid adaptive boosting - particle swarm optimization. Asian Journal of Civil Engineering, 2025; 26: 1059–1076. doi:10.1007/s42107-024-01233-3.

[11] Mahajan, A., Sharma, P. K. Machine learning-based prediction of high-strength concrete compressive strength incorporating limestone aggregates using ensemble and pruned tree models. Asian Journal of Civil Engineering, 2025; 26: 4595–4613. doi:10.1007/s42107-025-01445-1.

[12] Brahmeswari, L. C., Rao, B. D. V. C. M. Ultra-high performance concrete compressive strength prediction using machine learning boosting algorithms. Asian Journal of Civil Engineering, 2025; 26: 5139–5154. doi:10.1007/s42107-025-01476-8.

[13] Zviazhynski, B., White, C., Lees, J. M., Conduit, G. J. Predicting concrete strength using machine learning and fresh-state measurements. Data-Centric Engineering, 2025; 6: e37. doi:10.1017/dce.2025.10018.

[14] Mostofinejad, D., Bahmani, H., Eshaghi-Milasi, S., Nozhati, M. Empirical Relationships for Prediction of Mechanical Properties of High-Strength Concrete. Iranian Journal of Science and Technology, Transactions of Civil Engineering, 2023; 47: 315–332. doi:10.1007/s40996-022-01023-4.

[15] Iranian National Standardization Organization (INSO). 11268: Concrete – Measuring of temperature of freshly mixed hydraulic-cement concrete – Test method (2nd rev.). Tehran (IR): INSO; 2021.

[16] Iranian National Standardization Organization (INSO). 3201-1: Fresh concrete – Part 1: Sampling. Tehran (IR): INSO; 2010.

[17] Iranian National Standardization Organization (INSO). 3203-2: Fresh concrete – Part 2: Determining the consistency by slump – Test method (3rd rev.). Tehran (IR): INSO; 2023.

[18] Iranian National Standardization Organization (INSO). 3203-6: Fresh concrete – Part 6: Density – Test method (2nd rev.). Tehran (IR): INSO; 2025.

[19] Iranian National Standardization Organization (INSO). 1608-2: Hardened concrete – Part 2: Making and curing specimens for strength tests. Tehran (IR): INSO; 2023.

[20] ASTM International. C1064/C1064M-17: Standard test method for temperature of freshly mixed hydraulic-cement concrete. West Conshohocken (PA): ASTM; 2017. doi:10.1520/C1064_C1064M-17.

[21] European Committee for Standardization (CEN). EN 12350-2: Testing fresh concrete – Part 2: Slump test. Brussels (BE): EN; 2019.

[22] European Committee for Standardization (CEN). EN 12350-6: Testing fresh concrete – Part 6: Density. London (UK): EN; 2019.

[23] European Committee for Standardization (CEN). EN 12390-2: Testing hardened concrete – Part 2: Making and curing specimens for strength tests. Brussels (BE): EN; 2019.

[24] International Organization for Standardization (ISO). 1920-1: Testing of concrete – Part 1: Sampling of fresh concrete. Geneva (SW): ISO; 2004.

[25] Shapiro, S. S., Wilk, M. B. An analysis of variance test for normality (complete samples). Biometrika, 1965; 52: 591–611. doi:10.2307/2333709.

[26] Montgomery, D. C., Runger, G. C. Applied statistics and probability for engineers. 6th ed. Hoboken (NJ): John wiley and sons; 2014.

[27] Garbade, K. D. The initialization problem in variable parameter regression [PhD Thesis]. New York (NY): New York University, Graduate School of Business Administration; 1975.

[28] ASTM International. C192/C192M-24: Standard practice for making and curing concrete test specimens in the laboratory. West Conshohocken (PA): ASTM; 2024. doi:10.1520/C0192_C0192M-26.