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Machine Learning Model for Determining the 28-day Limit of Concrete Heat Release in Massive Monolithic Foundation Slabs

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Abstract

Introduction. Thermal cracking is a significant challenge for massive monolithic structures. The primary approach to mitigating this risk is to control the overall heat release during cement hydration. Published scientific papers address the direct problem of assessing thermal stresses under given conditions, including the exothermic properties of concrete mixtures. The objective of the study is to solve the inverse problem, that is, to create a reliable machine learning model to predict the 28-day maximum allowable total heat release (Q_{max}). Implementation of the proposed approach will enable monitoring the crack resistance of massive foundation slabs.

Materials and Methods. To build the machine learning model, a training dataset of 9375 samples was created using finite element parametric modeling. The model takes into account six input parameters: foundation slab thickness, upper surface heat transfer coefficient, ambient temperature, concrete compressive strength class, initial temperature, and concrete hardening rate. To improve forecast accuracy, the CatBoost (categorical boosting) algorithm was used with hyperparameters tuned by Bayesian optimization. Forecast quality was assessed using the mean absolute error, mean absolute percentage error, mean square error, root mean square error, and the coefficient of determination. The value of the parameters for forecasting was determined by a method based on the Shapley theory.

Results. The trained model demonstrated high accuracy. The mean absolute percentage error (MAPE) on the training set was 0.52%. The coefficient of determination was 0.99 on the training dataset, and 0.98 — on the independent test dataset. This indicated good agreement within the considered ranges of input parameters. Shap (Shapley additive explanations) analysis identified two key factors for Q_{max} : heat transfer coefficient and slab thickness (with significance values of 0.57 and 0.48, respectively). The parameters ranked by significance were as follows: surface heat transfer — 96%, slab thickness — 75%, ambient temperature — 61%, hardening rate — 35%, concrete grade — 17%, and initial temperature of the mix — 14%.

Discussion. The feature correlation was dictated by both the physical processes involved and the modeling methodology. The relatively high correlation between ambient temperature and initial mix temperature ($\rho = 0.63$) is explained by the conditions under which the model was trained. During dataset construction, the maximum initial concrete temperature was constrained by the ambient temperature. The weak positive correlation between concrete grade and Q_{max} is explained by the ability of high-strength concrete structures to withstand higher temperature gradients. Shap analysis allowed us to clarify: fast hardening at high temperatures reduced Q_{max} , while slow hardening at low temperatures increased it.

Conclusion. The machine learning model developed in this study provides an auxiliary computational framework for optimizing concrete composition selection during the design process. Bayesian optimization of hyperparameters provided high quality of algorithm performance in terms of metrics: MAE = 0.67; MSE = 1.78; RMSE = 1.33; MAPE = 0.52%. Three limitations of the model are unaccounted for fast-onset concrete creep, external deformation limitations, and cases of using slabs for transfer structures.

Keywords: heat release of concrete, crack formation in concrete slabs, guaranteed prediction of crack resistance, crack resistance criterion, selection of concrete composition in design

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Оригинальное эмпирическое исследование

Модель машинного обучения для определения предельно допустимого тепловыделения бетона к 28-м суткам в массивных монолитных фундаментных плитах

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Аннотация

Введение. Температурное трещинообразование представляет собой серьезную проблему для массивных монолитных конструкций. Главный метод снижения этого риска — контроль общего тепловыделения в процессе гидратации цемента. Опубликованные научные работы посвящены решению прямой задачи оценки температурных напряжений при заданных условиях, включая экзотермию бетонных смесей. Цель исследования — решение обратной задачи, т. е. создание надежной модели машинного обучения, способной прогнозировать максимально допустимое общее тепловыделение к возрасту 28 дней (Q_{max}). Реализация предложенного подхода позволит контролировать трещиностойкость массивных фундаментных плит.

Материалы и методы. Для построения модели машинного обучения сформировали обучающий датасет из 9375 образцов путем конечноэлементного параметрического моделирования. Модель учитывает шесть входных параметров: толщину фундаментной плиты, коэффициент теплоотдачи верхней поверхности, температуру окружающей среды, класс бетона по прочности на сжатие, начальную температуру и темп твердения бетона. Для повышения точности прогнозирования использовался алгоритм CatBoost¹ с гиперпараметрами, настроенными по байесовской оптимизации. Качество прогнозирования оценивали по средней абсолютной, средней абсолютной процентной, среднеквадратичной ошибке, корню из нее и коэффициенту детерминации. Ценность параметров для прогноза определили методом, основанным на теории Шепли.

Результаты исследования. Обученная модель продемонстрировала высокую точность. Средняя абсолютная процентная ошибка (MAPE)² на обучающем наборе — 0,52 %. Коэффициент детерминации — 0,99 на обучающем наборе данных и 0,98 — на независимом тестовом. Это указывает на хорошее соответствие в пределах рассмотренных диапазонов входных параметров. Анализ Shap³ выявил два главных фактора Q_{max} : коэффициент теплоотдачи и толщина плиты (значимость 0,57 и 0,48 соответственно). По значимости параметры распределились так: теплоотдача поверхности — 96 %, толщина плиты — 75 %, температура среды — 61 %, темп твердения — 35 %, класс бетона — 17 %, начальная температура смеси — 14 %.

Обсуждение. Корреляция признаков обусловлена особенностями физических процессов и моделирования. Значимый показатель для температуры окружающей среды и начальной температуры смеси ($\rho = 0,63$) объясняется условием обучения модели. При формировании датасета максимальная начальная температура бетона ограничивалась температурой окружающей среды. Слабая положительная связь класса бетона с Q_{max} объясняется способностью конструкций из высокопрочного бетона выдерживать более высокие температурные градиенты. Shap-анализ позволил уточнить: быстрое твердение при высокой температуре сокращает Q_{max} , а медленное при низкой температуре — увеличивает.

Заключение. Разработанная модель машинного обучения как вспомогательный вычислительный инструмент оптимизирует выбор состава бетона при проектировании. Байесовская оптимизация гиперпараметров обеспечила высокое качество работы алгоритма по метрикам: MAE = 0,67; MSE = 1,78; RMSE = 1,33; MAPE = 0,52 %. Три ограничения модели: неучтенные быстرونатекающая ползучесть бетона, внешние ограничения деформации и случаи использования плит для трансферных конструкций.

Ключевые слова: тепловыделение бетона, трещинообразование в бетонных плитах, гарантированное прогнозирование трещиностойкости, критерий трещиностойкости, выбор состава бетона при проектировании

¹ От англ. categorical boosting — категориальное повышение.

² От англ. mean absolute percentage error — средняя абсолютная процентная ошибка.

³ От англ. Shapley additive explanations — аддитивное объяснение на основе теории игр Шепли.

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Introduction. Crack resistance in massive monolithic reinforced concrete structures remains one of the most critical challenges in modern construction. The solution to this problem directly affects the durability and operational reliability of buildings and civil structures. Uneven temperature distribution and shrinkage deformations during concrete hardening are the key factors contributing to crack formation in early-age concrete [1]. To prevent defects, timely risk assessment is essential, and this issue is actively discussed in the literature. Thus, the algorithm from [2] allows concrete properties to be linked to the temperature field variation during hardening. The authors [3] investigate the temperature gradient in a massive monolithic slab based on field measurements, and demonstrate how the difference between the core and surface structures generates internal tensile stresses. In [4], with an emphasis on finite element modeling (FEM), the temperature gradients between the core and surface zones of the masses are analyzed. The results of three-dimensional calculations make it possible to formulate requirements for the mechanical properties of concrete and the temperature difference between the core and surface of a structure when modeling thermal stresses in the core — surface system [5]. In [6], a modern numerical phase field method is considered, which allows modeling the process of temperature crack formation and the dynamics of their development in massive concrete structures. The authors of this work introduce a criterion for comparing the calculated stresses and tensile strength of concrete.

In [7], methods for calculating the temperature field are considered. They take into account changes in the properties of concrete over time and such control measures as thermal insulation, modification of the mixture, and limitations of the temperature regime of concrete during placement. The authors [8] introduce strength criteria under thermal stress. In [9], the risk of early cracking is assessed based on temperature stresses.

The authors of the above publications address the direct problem of assessing the risk of early cracking in massive monolithic structures during construction, using parameters such as structural geometry, concrete heat release, mechanical properties, and heat transfer parameters. These approaches, based on FEM, allow for highly accurate assessment of cracking risk, but require significant computational resources, time, and detailed model tuning. This makes them unsuitable for rapid use during the preliminary selection of concrete mix design, when it is necessary to quickly evaluate numerous cement and additive options.

One of the highly efficient approach to minimizing the risk of early cracking in massive monolithic elements involves decreasing the specific heat release per 1 m³ of concrete mix. This value is determined by the cement content in 1 m³ of concrete mix and its mineralogical composition. To prevent early cracking in massive structures, low-exothermic cements are used, as well as additives that allow for a reduction in cement content while maintaining strength. A number of foreign researchers are focusing specifically on optimizing the composition of concrete mixtures for massive structures, paying particular attention to managing heat release during hydration through the use of supplementary cementitious materials (SCM) such as granulated blast furnace slag (GBFS), fly ash (FA), microsilica, and metakaolin [10].

Although supplementary cementitious materials significantly affect heat generation, the recommendations available in the literature on these processes remain primarily qualitative or only partially quantitative (for example, “replacing cement with 30% slag reduces heat generation by 15–20%”). Based on such approaches, it is difficult to obtain a specific numerical value for the maximum permissible heat generation Q_{max} for given geometric and climatic conditions. This difficulty is explained by the fact that the final permissible value depends on the complex interaction of a large number of parameters (slab geometry, environmental conditions, heat generation kinetics, initial mixture temperature, concrete strength class, etc.).

In [11], approaches to selecting the compositions of low-thermal mixtures with different proportions of GBFS and FA are considered. In [12], it is shown how heat generation and hardening kinetics depend on the degree of cement substitution. In [13], the effect of these factors on the development of thermal stresses is studied. The authors [14] offer a generalized review of the effect of different types of SCM on the heat of hydration. In [15], their impact on the microstructure of cement stone is considered. In [16], the formation of concrete strength at the early stages of hardening using SCM is analyzed.

Technical studies devoted to modeling the temperature field and stress development at an early age are discussed in detail in [17]. In [18], numerical methods for assessing the thermomechanical behavior of massive concrete structures are proposed. Study [19] develops this approach taking into account real heat generation parameters and mixture composition. The authors [20] write about the development of stable low-thermal compositions, including modern systems such as LC3 (Limestone Calcined Clay Cement), which demonstrate the potential for reducing the carbon footprint and hydration temperature while maintaining performance characteristics.

Practical recommendations for optimizing component proportions, including the use of ternary mixtures and low-carbon binder systems, are presented in [21]. Specific cement substitution ranges, laboratory testing methods, and examples of formulations that provide an optimal balance between reducing heat generation and maintaining strength characteristics are proposed in [22].

Despite the undeniable merits of these studies, they are typically focused on specific materials and conditions, and their results are not summarized in a compact predictive model suitable for engineering practice. Thus, a gap remains between:

- composition selection task (it is required to quickly estimate the permissible heat release);
- existing tools (labor-intensive FEM or experimental mixture preparation).

Thus, published studies offer:

- direct modeling of thermal stresses for given concrete properties (which requires considerable time and specialized software);
- prescription-based reduction of heat generation without reference to a specific permissible threshold determined by the structure geometry and heat exchange conditions.

At the composition selection stage, there is no tool available that would immediately answer the question: “What is the maximum allowable heat release by 28 days for a foundation slab with specified parameters to guarantee crack resistance?” This study aims to fill this gap. The research objective is to develop a predictive model for determining the acceptable heat release level that provides crack resistance for massive monolithic foundation slabs. Solving this problem is crucial when selecting the concrete mix for concreting massive monolithic structures. The maximum stress level (ratio of maximum tensile stress to tensile strength) is used as the crack resistance criterion. It should not exceed unity.

To achieve this goal, two sets of tasks were sequentially solved. The first was the development of an initial physicomaterial design model. Its three components are presented below:

- a one-dimensional finite element formulation of the thermal conductivity problem was selected, taking into account layer-by-layer concreting;
- the dependences of the thermophysical and mechanical properties of concrete on time and temperature (heat release function, hardening kinetics, strength, instantaneous modulus of elastic deformation) were specified;
- an algorithm for finding the maximum permissible heat release $Q_{\max}$ by the bisection method based on the criterion of a tensile stress level less than unity was implemented.

The second group of tasks involved constructing and testing a machine learning model. It had four components:

- a dataset of 9375 samples was generated through parametric finite element modeling;
- the CatBoost algorithm was selected and trained with hyperparameter optimization;
- accuracy was assessed on the training and test sets;
- shap interpretation of the model was performed.

Materials and Methods. The following physical, technical, and process parameters were selected as input:

- foundation slab thickness, h , m;
- heat transfer coefficient on the upper surface, α , $W/(m^2 \cdot ^\circ C)$;
- ambient temperature, T_{amb} , $^\circ C$;
- initial temperature of the concrete mix, T_0 , $^\circ C$;
- concrete compressive strength class, B , MPa (GOST 18105-2018⁴);
- hardening rate, which can take three values (1 — fast-hardening, 2 — normal-hardening, and 3 — slow-hardening).

The output variable was the maximum allowable total heat release of concrete during active cement hydration for 28 days ($Q_{\max}$, MJ/m³). The dataset size was 9375 samples obtained through numerical modeling and parametric analysis.

⁴ GOST 18105-2018 *Concretes. Rules for control and assessment of strength*. Garant. URL: <https://base.garant.ru/72932108/> (accessed: 02.03.2026).

When generating the training dataset, the thickness of the foundation slab ranged from 1 to 2 m in steps of 0.25 m. The heat transfer coefficient ranged from 3 to 23 W/(m²·°C) with a step of 5 W/(m²·°C). The ambient temperature ranged from 5 to 35°C with a step of 7.5°C. Concrete grades were B25, B30, B35, B40, B45. The heat release function was determined by equation [23]:

$$Q(t) = Q_{28} \exp \left(k \left(1 - \left(\frac{28}{t-b} \right)^x \right) \right), \quad (1)$$

where Q_{28} — heat release in MJ/m³ by the 28th day; t — time in days; k and x — parameters determining the heat release rate; $b = 4$ h — induction period.

The calculation of the thermal stress state was performed in a simplified formulation using the method given in [24]. It had previously been tested repeatedly using experimental data [25].

To calculate the temperature field, a one-dimensional heat transfer equation was used:

$$\lambda \frac{\partial^2 T}{\partial z^2} + W = \rho c \frac{\partial T}{\partial t}, \quad (2)$$

where λ — thermal conductivity coefficient; T — temperature; $W = \frac{\partial Q}{\partial t}$ — density of internal heat sources; ρ — density; c — specific heat capacity; t — time.

When calculating the temperature fields, the interaction of the slab with the soil mass, whose thickness was assumed to be constant and equal to 3 m, was taken into account. Thermophysical properties of concrete: $\rho = 2400$ kg/m³, $c = 1000$ J/(kg·°C), $\lambda = 2.67$ W/(m·°C). Thermophysical properties of the soil: $\rho_g = 1800$ kg/m³, $c_g = 750$ J/(kg·°C), $\lambda_g = 0.9$ W/(m·°C).

Boundary conditions for convective heat transfer were assumed on the slab surface:

$$\lambda \frac{\partial T}{\partial z} + \alpha (T - T_{amb}) = 0, \quad (3)$$

where α — heat transfer coefficient; T_{amb} — ambient temperature.

For simplicity, the temperature on the lower side of the soil mass was assumed to be equal to a constant value T_{amb} :

$$T_g(t) = T_{amb}. \quad (4)$$

The initial temperature of the entire soil mass was also assumed to be T_{amb} , and for concrete — the initial temperature of the concrete mix T_0 .

Equation (2) with boundary conditions (3) and (4) was solved by the finite element method. For this, a z - and t -dimensional mesh was introduced (40 finite elements across the slab thickness, 40 finite elements across the soil thickness, with 3000 time steps over the 28-day period). The duration and layering of the structure were taken into account when calculating the temperature fields and stresses. The layer thickness was assumed to be 0.25 m, and the laying time per layer was 2 hours. Before the layer's "birth", it was assigned:

- abnormally high thermal conductivity value — $\lambda = 1000$ W/(m·°C);
- zero heat capacity, which is physically equivalent to the absence of the layer.

After "birth", the layer was assigned its actual characteristics.

Before and for 12 hours after concrete placement, the foundation slab surface was assumed to be open, with free heat exchange with the environment and a heat transfer coefficient of 23 W/(m²·°C). After 12 hours, the heat transfer coefficient was assumed to be equal to the model input variable α . Calculations were performed using a program developed by the authors in the MATLAB environment.

When calculating the stress-strain state, the strength characteristics of concrete were represented as functions of its equivalent age t_{eq} , determined from the formula [26]:

$$t_{eq} = \frac{DM}{20}. \quad (5)$$

Here, DM — degree of maturity of concrete determined by the integral:

$$DM = \int_0^t T(\tau) d\tau, \quad (6)$$

where t — current moment in time, τ — integration variable, $T(\tau)$ — temperature at the moment in time τ .

The compressive strength of concrete R was determined by the formula [25]:

$$R = R_{28} \exp \left(s \left(1 - \sqrt{\frac{28}{t_{eq} - b}} \right) \right), \quad (7)$$

where $R_{28} = B + 12$ — compressive strength at 28 days; t_{eq} — equivalent age in days; $b = 0.167$ days = 4 h — induction period; s — coefficient depending on heat release kinetics.

Three concrete hardening rates were adopted: fast, normal, and slow. Table 1 presents the values of the coefficients k and x in formula (1), as well as the coefficient s in formula (7) for the three hardening rates.

Table 1

Heat Release Rate and Kinetics Parameters versus Hardening Rate

Hardening Rate	k	x	s
Fast (1)	0.14	0.40	0.20
Normal (2)	0.19	0.51	0.35
Slow (3)	0.24	0.62	0.50

Instantaneous modulus of elastic deformation of concrete E and its tensile strength R_t were determined through the compressive strength using the formulas [25]:

$$E = 22265 \cdot \left(\frac{R}{10} \right)^{0.28}, \quad (8)$$

$$R_t = 0.29 R^{0.6}. \quad (9)$$

Formula (8) was used to calculate the modulus of elasticity for an equivalent age of concrete of at least 12 hours. For an equivalent age of less than 12 hours, value E was assumed to be zero (it was considered that concrete before the age of 12 hours was not yet a solid body and there were no thermal stresses in it).

Stress increments $\Delta\sigma_x = \Delta\sigma_y = \Delta\sigma$ at each time step at all mesh nodes were calculated using the formula [24]:

$$\Delta\sigma = \frac{E(z, t)}{1 - \nu} (\Delta\varepsilon - \alpha_T \Delta T). \quad (10)$$

Here $\nu = 0.2$ — Poisson's ratio of concrete; $\alpha_T = 10^{-5} \text{ } 1/^\circ\text{C}$ — coefficient of linear thermal expansion; ΔT — change in temperature at the design node over time ΔT ; $\Delta\varepsilon$ — increment in total deformation, determined by the formula:

$$\Delta\varepsilon = \frac{\alpha_T \int_{-\frac{h}{2}}^{\frac{h}{2}} E(z, t) \Delta T(z) dz}{\int_{-\frac{h}{2}}^{\frac{h}{2}} E(z, t) dz}. \quad (11)$$

For each data set $[h \ \alpha \ T_{amb} \ B \ rate]$, the maximum permissible heat release value $Q_{max} = Q_{28}$ was determined at various initial concrete mix temperatures — from 5°C to T_{amb} . According to Code Specifications 70.13330.2012 (Load-Bearing and Separating Constructions), a value of 5°C corresponds to the minimum concrete mix temperature at the start of curing. This same regulatory document establishes the maximum concrete mix temperature. It should not exceed 30°C when concreting structures with a surface modulus greater than 3. The limit for massive structures with a surface modulus less than 3 is 25°C . However, in practice, the maximum temperature requirement is rarely met, thus, in the training dataset, the maximum value of T_0 was 35°C at the same ambient temperature. Specifying T_0 higher than T_{amb} (e.g., 35°C at $T_{amb} = 5^\circ\text{C}$) would be physically unreasonable and would contradict regulatory requirements. In this study, we do not consider winter concreting with preheated concrete mix, as evident from the minimum ambient temperature taken into account (5°C).

Using the bisection method, $Q_{max} = f(h, \alpha, T_{amb}, T_0, B, rate)$ was determined for the given values of the input variables from the training set. The search for value Q_{28} in the range from 20 to 520 MJ/m^3 , was performed under the condition that the maximum tensile stress ratio σ/R_t was equal to unity. The bisection method was applied with an allowable error of 1% in finding Q_{max} .

The range from 20 to 520 MJ/m³ was selected for the following reasons. According to [27], the specific heat release of Portland cement at the age of 28 days can take values from 120 to 513 kJ/kg. The cement content in concrete can vary from 200 to 600 kg/m³ (SNiP 5.01.23-83⁵). As a result, for the lower limit of Q_{28} , $120 \text{ kJ/kg} \cdot 200 \text{ kg/m}^3 = 24 \text{ MJ/m}^3$ was obtained. This value was rounded to 20 MJ/m³. The upper limit was $513 \text{ kJ/kg} \cdot 600 \text{ kg/m}^3 = 308 \text{ MJ/m}^3$. However, some cements, such as prestressed cements, have higher heat release than Portland cement. The difference can be as much as twofold. Therefore, the upper limit was adjusted upward.

Table 2 partially presents the resulting dataset for training the artificial intelligence model.

Table 2

Initial Data for Model Training

No.	h , m	α , W/(m ² ·°C)	T_{amb} , °C	T_0 , °C	B , MPa	rate	Q_{max} , MJ/m ³
1	1	3	5	5	25	1	302.2265625
2	1	3	5	5	25	2	325.6640625
3	1	3	5	5	25	3	298.3203125
4	1	3	5	5	30	1	310.0390625
5	1	3	5	5	30	2	335.4296875
6	1	3	5	5	30	3	310.0390625
7	1	3	5	5	35	1	317.8515625
8	1	3	5	5	35	2	343.2421875
9	1	3	5	5	35	3	321.7578125
10	1	3	5	5	40	1	323.7109375
11	1	3	5	5	40	2	351.0546875
12	1	3	5	5	40	3	333.4765625
13	1	3	5	5	45	1	327.6171875
...	...	...	...	...	...	...	...
2341	1.25	8	12.5	5	45	3	136.6992188
2342	1.25	8	12.5	6.875	25	1	168.9257813
2343	1.25	8	12.5	6.875	25	2	167.9492188
2344	1.25	8	12.5	6.875	25	3	120.0976563
2345	1.25	8	12.5	6.875	30	1	177.7148438
2346	1.25	8	12.5	6.875	30	2	175.7617188
2347	1.25	8	12.5	6.875	30	3	125.9570313
2348	1.25	8	12.5	6.875	35	1	185.5273438
2349	1.25	8	12.5	6.875	35	2	183.5742188
...	...	...	...	...	...	...	...
9366	2	23	35	35	30	3	64.67773438
9367	2	23	35	35	35	1	62.72460938
9368	2	23	35	35	35	2	78.34960938
9369	2	23	35	35	35	3	66.63085938
9370	2	23	35	35	40	1	64.67773438
9371	2	23	35	35	40	2	81.27929688
9372	2	23	35	35	40	3	69.07226563
9373	2	23	35	35	45	1	66.63085938
9374	2	23	35	35	45	2	83.72070313
9375	2	23	35	35	45	3	71.02539063

⁵ SNiP 5.01.23-83. *Standard rates of cement consumption for the preparation of precast and monolithic concrete, reinforced concrete products and structures*. Moscow: Stroizdat, 1985. (In Russ.)

As we can see, the resulting dataset consists of six input features and one target variable. To build and validate the model, the entire dataset was divided into training and test sets. The ratio generation procedure was 80/20, with multiple cross-validation performed using the Repeated k-Fold Cross-Validation system ($k = 5$) with a fixed initial random number generator parameter (random_state = 42).

Before splitting, the values were checked for correctness and the consistency of the variable dimensions. The “rate” feature was converted to an ordinal variable according to Table 1. Thus, with a total sample size of 9375 observations, the quantitative component of the training sample was 7500 records for model training and 1875 records for its validation. The test sample data was used only once to evaluate the generalization ability of the model.

The statistical characteristics of the original dataset are summarized in Table 3. The ranges of variation of the input and output parameters are also presented. Key indicators include sample size, sample mean, dispersion, and extreme values of variables. These indicators, taken together, help conduct statistical analysis of the variables, determine their dispersion relative to the core, demonstrate distribution asymmetry, and derive distribution laws for the data of the variation series.

Table 3

Original Dataset Statistical Characteristics

Parameter	h , m	α , W/(m ² ·°C)	T_{amb} , °C	T_0 , °C	B , MPa	rate	Q_{max} , MJ/m ³
Average	1.50	13.00	20.00	12.50	35.00	2.00	129.00
Standard deviation	0.35	7.07	10.61	8.39	7.07	0.82	51.36
Min	1.00	3.00	5.00	5.00	25.00	1.00	38.68
25 %	1.25	8.00	12.50	5.00	30.00	1.00	92.51
50 %	1.50	13.00	20.00	10.62	35.00	2.00	116.19
75 %	1.75	18.00	27.50	16.25	40.00	3.00	154.28
Max	2.00	23.00	35.00	35.00	45.00	3.00	35.87

Machine learning can be viewed as multidimensional interpolation. Hence, the model dependable operation is guaranteed exclusively within the domain of the input parameters represented in the training dataset. The minimum and maximum input parameter values listed in Table 3 cover the range of the most common characteristics of massive monolithic foundation slabs.

To improve the quality of the models, correlations between variables were analyzed. Gradient Boosting and CatBoostRegressor, implemented via the CatBoost library, were used to analyze data and build a model predicting the maximum permissible concrete heat generation in massive monolithic foundation slab construction. Random search and Bayesian optimization methods were used to optimize the model hyperparameters.

Gradient boosting model parameter values for regression (CatBoostRegressor):

- iterations (number of iterations) — 600–2000;
- depth (depth of learning) — 4–12;
- learning_rate (training speed) — 0.01–0.09;
- L2_reg_lambda (variable regularization coefficient of the L2 loss function) — 0.001–0.009.

The forecast quality was assessed using the metrics MAE (mean absolute error), MSE (mean square error), MAPE (mean absolute percentage error), RMSE (root mean square error), and coefficient of determination R^2 .

To interpret the impact of the parameters under consideration on the model predicted value, a visual feature influence method (Shap summary plot), based on the Shapley theory, was used. This method allows evaluating not only the significance of each parameter contribution to the final model prediction but also determining the direction of its influence. Key properties were used in constructing the Shap summary plot: local accuracy, linearity, symmetry, and the absence of a missing feature effect (the contribution of a missing feature is zero). This approach demonstrates how much the prediction results change when changing the values of a specific parameter.

Research Results. Figure 1 shows the correlation between the input and output parameters of the model. With the exception of the initial concrete mix temperature and ambient temperature, there is no correlation between the remaining input parameters, indicating their independence.

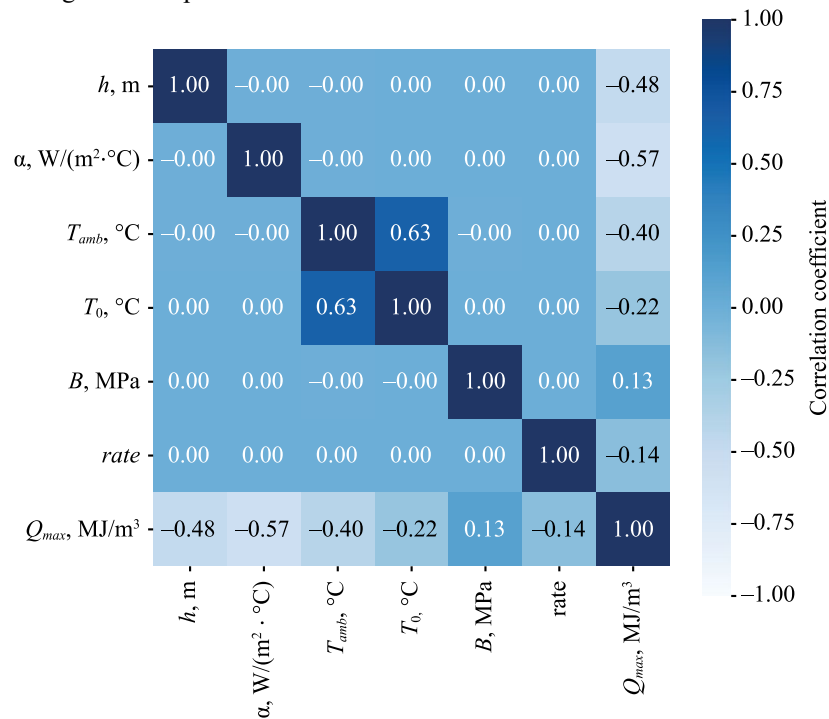


Fig. 1. Correlation matrix

The initial concrete temperature parameter has a significant correlation with the ambient temperature ($\rho = 0.63$). Weak to moderate correlation is observed between the maximum heat release of concrete and the model input parameters:

- foundation slab thickness ($\rho_{h/Q_{max}} = 0.48$);
- heat transfer coefficient on the upper surface ($\rho_{\alpha/Q_{max}} = 0.57$).

The quantitative significance of the model parameters by degree of significance is clearly shown in Figure 2:

- surface heat transfer coefficient — 96%;
- foundation slab thickness — 75%;
- ambient temperature — 61%;
- hardening rate — 35%;
- concrete grade — 17%;
- initial temperature of the concrete mix — 14%.

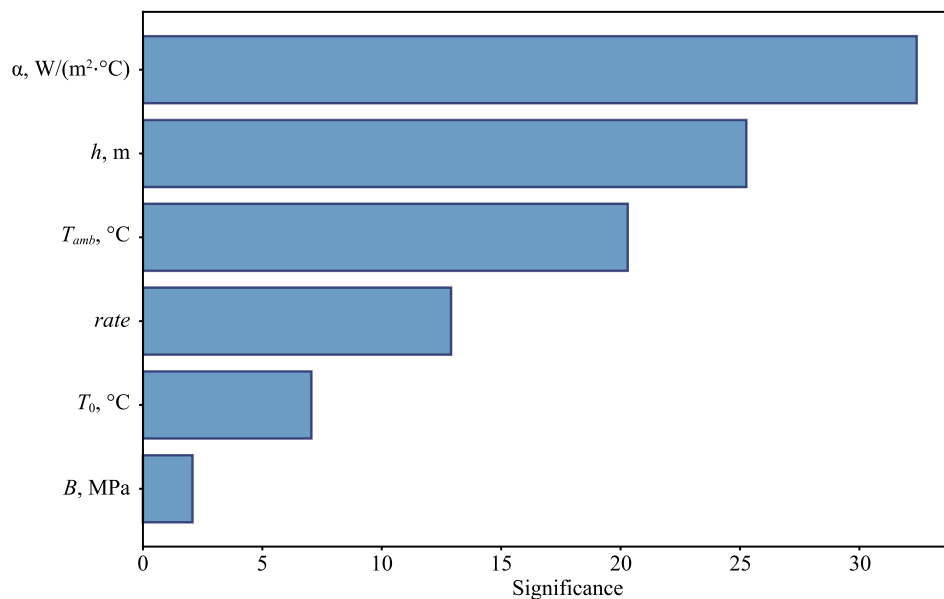


Fig. 2. Average absolute influence of features on the output variable

The optimal values of the parameters obtained during the model training process are presented in Table 4.

Table 4

Optimal Values of Model Parameters

Model	Parameter	Value
CatBoost	Iterations (number of iterations)	1488
	Depth (depth of learning)	8
	Learning rate	0.06
	L2 leaf reg (L2- regularization to prevent overfitting)	0.006

The performance metrics of the algorithm are given in Table 5.

Table 5

Model Quality Metrics

Metric/Model	Value
MAE	0.67
MSE	1.53
RMSE	1.33
MAPE, %	0.52
R^2_{train} (training)	0.99
R^2_{test} (testing)	0.98

Visualization of the predictions for the training and test sets is shown in Figures 3 and 4, respectively. The target values T of the output parameter are plotted on the abscissa axis, and the predicted values P are plotted on the ordinate axis. All points are located very close to the straight line $P = T$, indicating very high prediction quality.

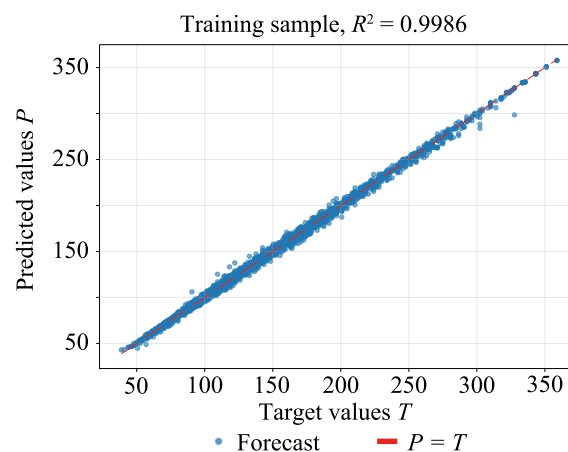


Fig. 3. Forecast error graph for the training sample

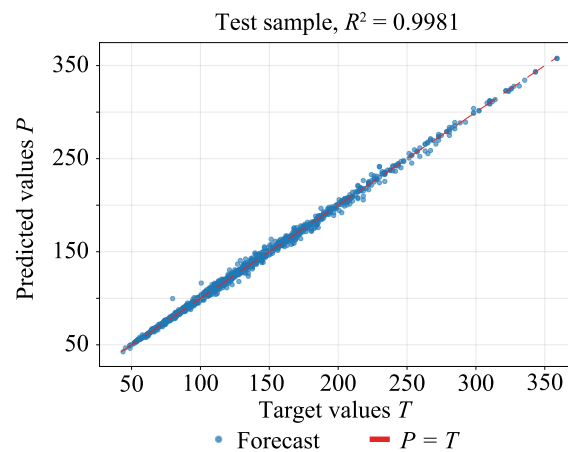


Fig. 4. Forecast error graph for the test sample

Discussion. The significant correlation between ambient temperature and the initial concrete temperature ($\rho = 0.63$) is explained by the fact that the upper limit of the initial concrete temperature was limited by the ambient temperature when generating the training dataset. The presence of weak or moderate correlation between the input parameters and the maximum heat release of concrete indicates a complex interaction between individual model parameters. The effect of parameters on Q_{max} can be nonlinear or interdependent. For example, slab thickness interacts with the heat transfer coefficient on the surface. With a large slab thickness, heat transfer from the surface is impeded, resulting in heat accumulation within the structure. However, with a higher heat transfer coefficient, heat is dissipated more quickly, reducing the risk of overheating.

All input parameters, with the exception of concrete grade, show a negative correlation with the output parameter Q_{max} . This is consistent with the physics of the process.

A reduction of the ambient temperature and the initial temperature of the concrete mix, while maintaining the heat release, results in a decrease in the maximum stress level. A well-known technique is adding ice to the concrete mix when working in hot climates [28]. Direct injection of liquid nitrogen into the tanks of concrete mixers is becoming an increasingly popular cooling method [29]. Consequently, with the stress level remaining constant, a decrease in the values T_{amb} and T_0 will provide an increase in the permissible value Q_{max} .

The weak positive correlation between concrete grade and maximum permissible heat release arises because the use of higher-grade concretes results in an increase in tensile strength alongside compressive strength, thereby enabling structures to tolerate larger temperature gradients.

To better interpret the forecast results, an alternative approach to analyzing model features — Shap summary plot — was also considered. This method clearly demonstrated the significance of features, the direction of their effect, and the distribution of their contributions to the target variable values (Fig. 5).

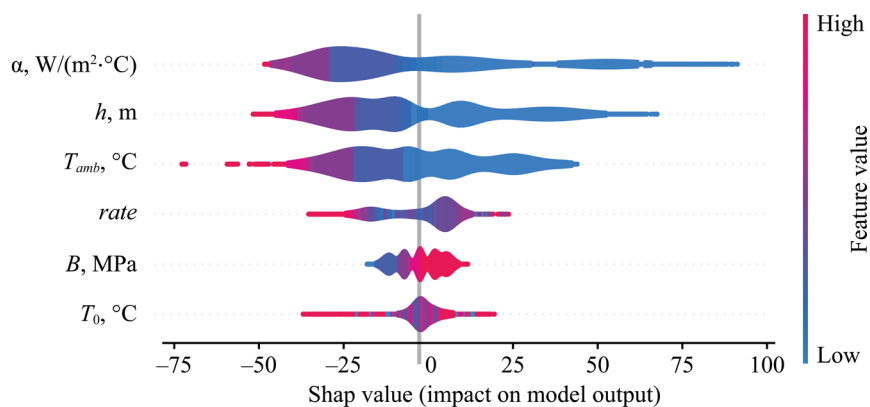


Fig. 5. Assessment of significance of model features

Analysis of the Shap-graph showed that the greatest effect on the maximum permissible total heat release was exerted by the slab thickness and the heat transfer coefficient, which determined the intensity of heat removal and the distribution of the temperature field between the core and surface zones. As the thickness of the structure of massive monolithic slabs increased, the thermal gradient grew, and the stress in the surface layers increased, which resulted in a decrease in the permissible heat release. The ambient temperature parameter demonstrated less significance. Its relationship with the rate of concrete hardening is particularly significant:

- accelerated hardening at high ambient temperatures reduces the maximum allowable heat release of concrete;
- slow hardening at low ambient temperatures increases the maximum allowable heat release of concrete.

Overall, the trend in the effect of the attributes, determined by the analysis of Shap values, coincides with the results of the correlation analysis.

Conclusion. Most input parameters in the tested model for predicting concrete maximum allowable heat release show weak correlation, indicating that each factor independently contributes to thermal stress formation during construction of massive monolithic foundation slabs. This suggests a complex, nonlinear interaction of variables, in which the risk of early cracking in massive monolithic structures is determined not by a single dominant parameter, but by their multifactorial impact.

Hyperparameter tuning via Bayesian search methods resulted in high algorithm quality as measured by the specified metrics: MAE = 0.67; MSE = 1.78; RMSE = 1.33; MAPE = 0.52%.

Shap analysis of the thermal stress state calculations for structures, considering both time-dependent and temperature-dependent strength properties of concrete, enabled the contribution of each input parameter to the final predictions to be determined. The most significant are the foundation slab thickness and the surface heat transfer coefficient. These parameters have the greatest impact on whether heat generation will reach the permissible maximum.

A comprehensive approach to predicting the maximum allowable heat release of concrete during the construction of massive monolithic foundation slabs has been developed, based on a combination of finite element modeling and machine learning methods.

The proposed machine learning model can be used at the preliminary stage of concrete mix design to estimate the maximum permissible cement consumption. However, further validation using experimental data is required for widespread implementation in design practice.

The limitations of the present model must also be acknowledged.

1. When training the model, stress levels were determined without taking into account the fast-onset creep of concrete. The true stress level, when creep is taken into account, will be lower than the calculated value, thus, the developed model predicts the permissible heat release level with some margin. Further research could focus on incorporating creep into predictive models.

2. The developed model is applicable to structures in which thermal stresses are caused solely by so-called internal deformation constraints (cross-sections remain flat despite unequal thermal deformations along the cross-section height). In addition to internal constraints, the structure may also experience external deformation constraints, such as when a slab is erected on a bedrock foundation and is rigidly connected to it, limiting the total deformations. The proposed model is not applicable to structures subject to external deformation constraints. In such structures, the risk of early crack formation can only be assessed through a comprehensive 3D finite element analysis.

3. In addition to foundations, massive slabs are used as transfer structures, providing interaction between misaligned columns in the above- and below-ground parts of a building. In this case, the boundary conditions are different (instead of interaction with the soil mass on the lower surface, heat exchange with the environment occurs). The development of predictive models for such structures can also be noted as a promising area for further research.

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