Advances in Science and Technology Research Journal

Advances in Science and Technology Research Journal, 2026, 20(10), 481–490
https://doi.org/10.12913/22998624/225222
ISSN 2299-8624, License CC-BY 4.0

Received: 2026.05.15
Accepted: 2026.07.18
Published: 2026.09.01

Integrating hydration heat kinetics with artificial neural networks: A maturity model for prediction of ordinary Portland cement mortar strength development

Jerzy Wawrzeńczyk[1], Adam Kłak[1*], Aneta Śluzek[1]

[1] Department of Civil Engineering and Architecture, Kielce University of Technology, Aleja Tysiaclecia Panstwa Polskiego 7, Kielce, Poland

* Corresponding author's e-mail: adamklak@tu.kielce.pl

ABSTRACT

Conventional maturity methods estimate strength from temperature–time histories using equivalent age and apparent activation energy (Ea). However, determining Ea is time-consuming and requires extensive experimental testing. Moreover, its value depends on cement composition, mixture proportions, and curing conditions, which limits the applicability of traditional maturity-based approaches. This study proposed a new maturity-based methodology for predicting the OPC concrete compressive strength development. The proposed approach eliminates both the calculation of equivalent age and the need to determine activation energy. The novelty of the work does not lie in the use of artificial neural networks (ANNs) alone. The main contribution is the integration of the maturity concept with the hydration heat parameters obtained from isothermal calorimetry. Cement hydration is characterized by two calorimetric parameters: the cumulative heat released after 12 h (Q_{12}) and after 48 h (Q_{48}). These parameters describe both the rate and the extent of hydration. They are combined with curing temperature history and water-to-cement ratio in an artificial neural network model. The experimental program included seven cements produced at four cement plants. Mortars were cured under different temperature conditions and with different water-to-cement ratios. Calorimetric measurements showed that Q_{12} and Q_{48} were only slightly affected by the changes in the water-to-cement ratio. Therefore, the same hydration descriptors could be used for a wider range of mortar compositions. The developed ANN model successfully captured the nonlinear relationship between hydration characteristics, curing conditions, and compressive strength development. Good agreement was obtained between the measured and predicted strength values. The scientific contribution of this study is the development of a new maturity-based framework that replaces activation-energy-dependent formulations with calorimetrically determined hydration heat descriptors. The proposed methodology combines maturity theory, hydration heat kinetics, and artificial neural networks into a single predictive tool. This approach simplifies practical implementation and improves the prediction of strength development in the cementitious materials exposed to variable curing conditions.

Keywords: mortar, concrete, maturity method, compressive strength development, artificial neural networks.

INTRODUCTION

Accurate prediction of early-age compressive strength is one of the key issues in concrete technology, because it directly affects construction safety, quality control, scheduling of construction operations, and overall project costs. Reliable estimation of strength development enables optimization of formwork removal, prestressing operations, and other construction activities while reducing unnecessary delays. Consequently, maturity-based methods have become widely accepted engineering tools for estimating in-place concrete strength under variable curing conditions.

Among the available maturity formulations, the equivalent age concept proposed by Hansen and Pedersen [1] is regarded as one of the most important developments in maturity theory. The method relates strength development to the combined influence of curing time and temperature by introducing the concept of apparent activation energy (Ea), which describes the temperature sensitivity of cement hydration. Owing to its simplicity and practical applicability, the Hansen–Pedersen approach has become the basis for numerous maturity models and has been incorporated into engineering practice.

Saadoon et al. [2] proposed a methodology for estimating the apparent activation energy of conventional and rapid-hardening concretes and demonstrated that this parameter strongly influences the accuracy of maturity-based strength prediction. ASTM C1074 [3] also recommends determining the apparent activation energy experimentally whenever greater prediction accuracy is required, because the use of default values may lead to significant prediction errors.

Although maturity methods are well established, the determination of apparent activation energy remains one of their principal limitations. The procedure recommended in ASTM C1074 requires preparing numerous specimens, curing them under different temperature conditions, and performing repeated compressive strength tests over several weeks. Consequently, the calibration process is labor-intensive, time-consuming, and relatively expensive.

Several researchers have demonstrated that the apparent activation energy should not be regarded as a universal material constant. RILEM TC119-TCE [4] indicated that activation energy depends on the characteristics of the cementitious system and should be carefully considered in the thermal analyses of early-age concrete. Kaszyńska [5] reported that the apparent activation energy varies with concrete composition, particularly in high-performance concretes. Lachemi et al. [6] confirmed that different cement systems require individual calibration of maturity relationships. Chanvillard and D'Aloia [7] showed that activation energy cannot generally be assumed constant throughout the hydration process, whereas Kada-Benameur et al. [8] demonstrated that its value remains relatively stable only within a limited range of hydration. Jonasson et al. [9] further proposed a nonlinear relationship describing the influence of curing temperature on activation energy. Carino and Tank [10] developed maturity functions for concretes produced with different cements and admixtures, highlighting the importance of proper calibration of maturity parameters. Kurdowski and Pichniarczyk [11] also discussed the limitations of the Arrhenius equation when applied to concrete maturity assessment. D'Aloia and Chanvillard [12] later proposed numerical procedures for estimating apparent activation energy based on hydration modeling.

An alternative approach to characterizing cement hydration consists in using calorimetric measurements. Kuryłowicz-Cudowska [13] compared the activation energy determined from calorimetry with the values obtained from mechanical testing and concluded that calorimetric measurements provide superior repeatability and measurement precision. Wirquin et al. [14] also demonstrated that calorimetry offers an effective method for characterizing cement hydration while reducing experimental uncertainty.

The relationship between hydration heat and strength development has been recognized for several decades. Venuat [15] was among the first researchers to demonstrate that cumulative hydration heat can be used to estimate subsequent mortar strength. Bobrowicz [16] confirmed this relationship for the mortars cured at reduced temperatures and showed that hydration heat remained closely correlated with compressive strength. Ge et al. [17] investigated several cement types and demonstrated that isothermal calorimetry provides valuable information for predicting the mechanical behavior of cementitious materials. Bentz et al. [18] analyzed more than 200 mortar mixtures and reported a strong relationship between hydration heat and compressive strength, particularly after normalization with respect to the amount of mixing water. Baran and Pichniarczyk [19] performed a statistical evaluation using cements produced at nine Polish cement plants and confirmed that hydration heat can serve as a reliable indicator of compressive strength.

More recently, Beskopylny et al. [20] developed predictive models describing the formation of calcium silicate hydrate (C–S–H) based on SEM and EDS analyses. Although their work focused on microstructural evolution rather than maturity modeling, it confirmed that the development of hydration products can be successfully represented using predictive modeling techniques. Their study further emphasizes that hydration characteristics constitute a physically meaningful basis for predicting the mechanical performance of cementitious materials.

Boubekeur et al. [21] proposed an empirical relationship between hydration heat and early-age strength for blended cement mortars cured at constant temperatures. Their results demonstrated that calorimetric measurements can successfully replace more laborious experimental procedures during the early stages of strength development. Rizal et al. [22] further showed that the combined use of silica fume and polycarboxylate-based superplasticizers significantly affects early compressive strength, emphasizing that hydration kinetics and mixture composition must be considered simultaneously when developing predictive models.

Solomon and Ratajczak [23] recently compared different maturity models for concretes produced with various cement types and demonstrated that hydration heat, maturity development, as well as early-age strength are closely interconnected. Their study also highlighted the practical importance of reliable strength prediction in optimizing construction processes and reducing the environmental impact of concrete production. From a broader perspective, Safran et al. [24] emphasized that the technologies improving construction efficiency contribute simultaneously to environmental, economic, and social sustainability, demonstrating the engineering importance of reliable predictive methodologies.

Artificial neural networks have been increasingly applied in concrete technology because of their capability to represent complex nonlinear relationships between multiple variables without assuming predefined analytical functions. In most published studies, however, ANNs were employed primarily as purely data-driven prediction tools, whereas the physical characteristics of cement hydration received considerably less attention.

In authors' previous work [25], an artificial neural network model combining apparent activation energy and cumulative hydration heat released after 48 hours was developed for predicting mortar strength development. Although satisfactory prediction accuracy was achieved, the methodology still required experimental determination of apparent activation energy and was limited to a single water-to-cement ratio, reducing its practical applicability.

The present study proposed a different maturity-based framework. The novelty of this work does not lie in the application of artificial neural networks themselves, since ANN techniques are already well established in civil engineering. Instead, the principal scientific contribution is the replacement of the apparent activation energy and equivalent-age concept with two calorimetrically determined hydration descriptors: the cumulative heat released after 12 hours (Q_{12}) and after 48 hours (Q_{48}). These parameters characterize both the kinetics and the advancement of cement hydration and can be obtained from a single three-day isothermal calorimetric test.

The proposed methodology integrates these experimentally determined hydration descriptors with curing temperature history and water-to-cement ratio within an artificial neural network model. Consequently, ANN serves only as a nonlinear computational tool, whereas the physical relationship between cement hydration and strength development is preserved. The objective of this study was therefore to develop and validate a practical maturity-based methodology capable of predicting compressive strength development of Portland cement mortars while eliminating the need for determining apparent activation energy, thereby significantly simplifying the experimental calibration required by conventional maturity methods.

EXPERIMENTAL PROGRAM

The main objective was to include in the strength–maturity calculations two parameters that characterized both the magnitude and the kinetics of heat evolution during hydration of a given cement, as determined by microcalorimetry. The conceptual scheme was presented in Figure 1.

The analysis covered two cements originating from the same production plant, although they belong to different strength classes. The materials exhibit differences not only in the cumulative heat released after 72 hours of hydration (b), but also in the kinetics of heat evolution (a). Such variations in thermal behavior are reflected in the rate at which compressive strength develops during the curing process (c).

Materials

The following materials were used:

- As specified in the Polish standard, quartz sand with particle sizes ranging from 0 to 2 mm was used.

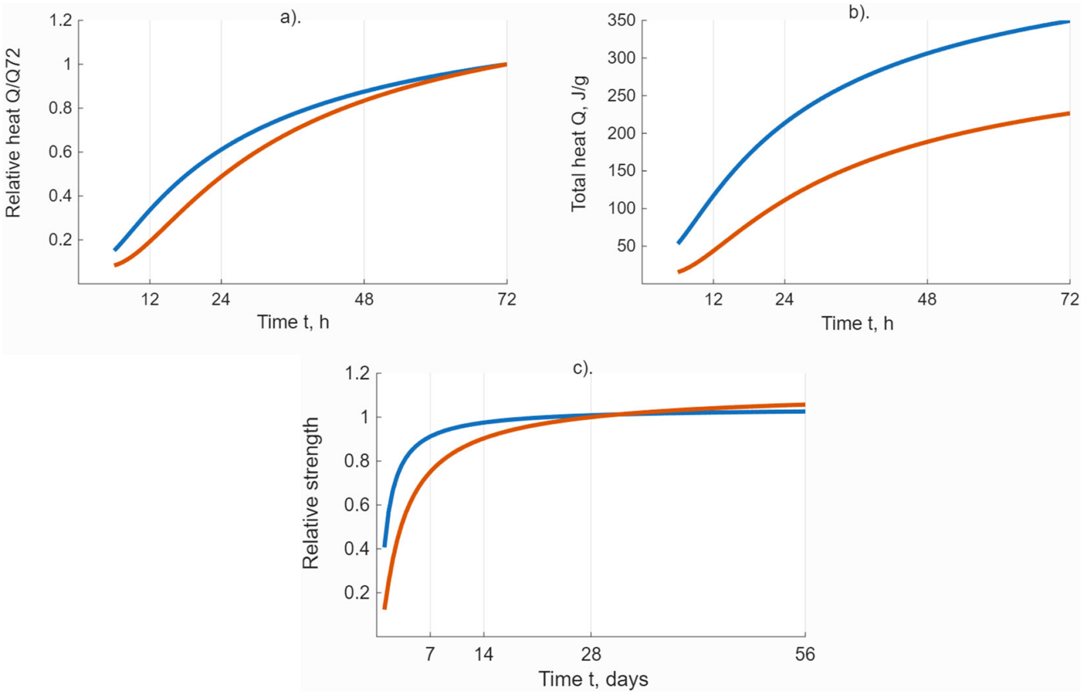

Figure 1. Conceptual diagram illustrating the effect of amount and rate of hydration heat evolution the compressive strength development of mortars made with two different Portland cements

- Seven Portland cements produced at four cement plants in Poland (classified as A, B, C, D), covering compressive strength classes 32.5–52.5 (symbols 32, 42, 52).
- A polycarboxylate ether plasticizer (Table 1).

The sample preparation procedure

Mortar testing followed the procedure specified in ASTM C1074-04 [3]. The experimental work was organized in two stages. The initial phase, previously described in [25], involved the preparation of mortar specimens using cements A32, A42, B42, B52, and C42, while maintaining a constant water-to-cement ratio of 0.45. All specimens in this stage were cured in water baths controlled at 5 °C, 20 °C, and 35 °C, and the corresponding results were reported in [25]. In the subsequent phase, the scope of the study was expanded by introducing additional mortar compositions with W/C ratios of 0.40, 0.45, and 0.50. Three reference concrete mix designs were selected, and the mortar formulations were adjusted to remain consistent with them, ensuring identical fine aggregate-to-cement ratios, water-to-cement ratios, and plasticizer dosages relative to cement as in the parent concrete mixtures. Mixing and specimen casting were carried out under laboratory conditions at approximately 22 °C.

Table 1. The variables of the experiment.

Mix #	Cement type	W/C ratio	Temperature „T”	Q_{12}	Q_{48}
A32	CEM I 32.5R	0.45	5; 20; 35	47	197
A42	CEM I 42.5R	0.45	5; 20; 35	65	214
B42	CEM I 42.5R	0.45	5; 20; 35	46	191
B52	CEM I 52.5R	0.45	5; 20; 35	111	302
C42	CEM I 42.5R	0.45	5; 20; 35	75	245
D42	CEM I 42.5R	0.40; 0.45; 0.50	10; 20; 30	71	211
D52	CEM II/ALL-52.5	0.40; 0.45; 0.50	10; 20; 30	92	246

Note: Q_{12} – The heat of hydration in the first 12 hours in [kJ/kg]; Q_{48} – The heat of hydration in the first 48 hours in [kJ/kg].

The mortars were mixed in a laboratory mixer with adjustable rotational speed and mixing time. All mixtures were prepared using an identical mixing protocol. Cement, water, and admixture were initially mixed for 30 s at 140 rpm. Sand was then added gradually during the following 30 s at the same speed. Mixing continued for 30 s at 285 rpm, after which the mixture was allowed to rest for 90 s. A final mixing stage of 60 s at 285 rpm was applied before specimen casting. Overall, seven mortar series were produced, each associated with a specific cement type and labeled A–D. For every series, about 15 dm³ of fresh mortar was prepared and cast into 15 molds, each mold containing three prismatic specimens with dimensions 40 × 40 × 160 mm, yielding a total of 45 specimens per series. After casting, the specimens were divided into three equal groups and placed into separate curing setups consisting of five molds each. Immediate curing was performed in water baths maintained at 5 (10) °C, 20 °C, and 35 (30) °C. The molds were partially submerged to approximately mid-height to ensure rapid thermal stabilization of the material. After 1–2 days, demolding was carried out, and the specimens were returned to the water baths for continued curing until the time of compressive strength testing. During the entire storage period, the water was continuously circulated and kept at the target temperature.

Compressive strength

Compressive strength testing of hardened mortars was performed following PN-EN 196-1. For every mortar composition, measurements were carried out after 1, 3, 7, 14, 28, and 56 days of curing, as described previously in [25]. During the entire curing period, the specimens were stored in temperature-controlled water baths corresponding to the assigned test conditions. The final strength value used in the analysis was calculated as the average of four test results.

Calorimetric tests

A three-channel TAM Air isothermal calorimeter was used to perform all experiments at a constant temperature of 20 °C. The heat evolution data were monitored continuously over a period of 72 hours and recorded using a dedicated computer-based acquisition system. For every test, one specimen and one reference were analyzed simultaneously. An inert quartz sand–water mixture served as the reference material, chosen because its thermal capacity closely matched that of the investigated cement paste. This configuration provided a stable instrumental baseline and enhanced the overall reliability of the calorimetric results.

RESULTS AND DISCUSSION

Hydration heat

The development of cement hydration for pastes is shown in Figure 2.

To characterize both the extent and the rate of hydration heat evolution, two indicators derived from Figure 2 were selected: the cumulative heat measured after 12 h (Q_{12}) and after 48 h (Q_{48}). A summary of these values for all investigated cements is provided in Table 2. Only minor differences were observed between cement pastes

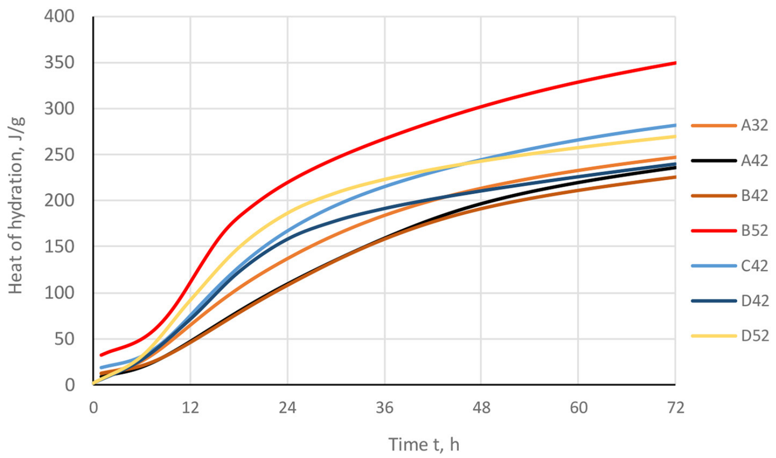

Figure 2. Results of calorimetric tests showing the heat of hydration over 72 h

prepared with different W/C ratios. Therefore, for further calculations, average values obtained from three measurements were adopted. This result supports the proposed modeling strategy, since it demonstrates that the same calorimetric descriptors (Q_{12} and Q_{48}) can be assigned to a given cement regardless of mixture water content. Consequently, the developed model can capture the strength variations associated with a wider range of mortar compositions.

Compressive strength of mortar samples

The compressive strength data for the mortars produced in the initial stage of the experimental work have already been published in [25]. The results obtained from the second phase, which included the additional mortar mixtures, are presented separately in Figure 3.

The assembled dataset containing the information on cement composition, heat of hydration (Q_{12} and Q_{48}), curing temperature history, and compressive strength results includes 193 records. The dataset was randomly divided into training and testing subsets. A total of 173 records were used for network training, while the remaining 20 records were reserved for independent testing and validation of the model performance. This dataset was subsequently subjected to further analysis.

ANN model for prediction of strength development

Considering that five input factors affect the compressive strength of hardened mortar, describing these relationships using classical statistical regression methods is difficult, since the

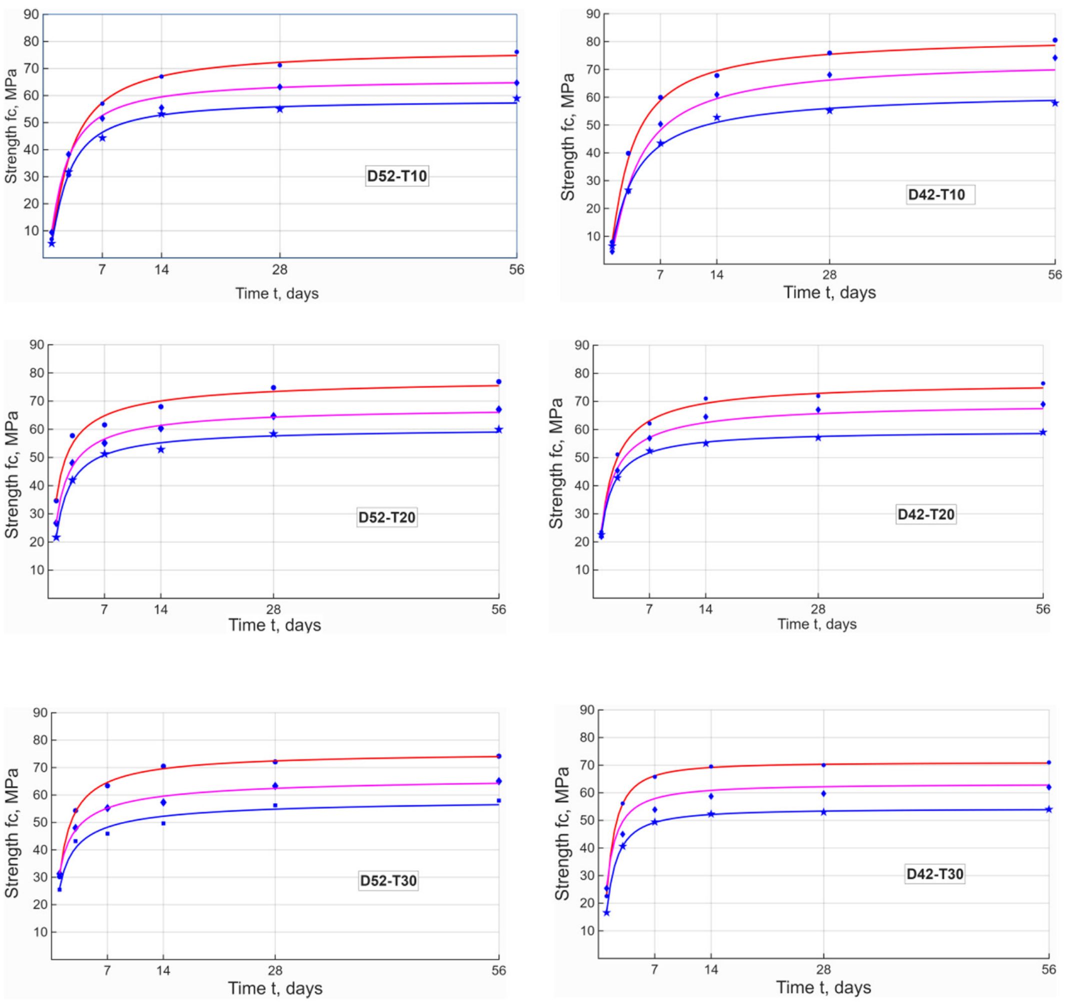

Figure 3. Development of compressive strength of the mortars made with cements D42 and D52 as a function of curing temperature (T10, T20, and T30 °C) and W/C ratio (solid lines represent the obtained functional relationships)

analytical form of these functions is unknown. It was therefore concluded that a more suitable approach is the application of artificial neural network (ANN) techniques. An attempt was thus made to apply ANN analysis using MATLAB software [26]. In this approach, the ANN method serves as an alternative to multivariate regression analysis. The developed neural network represents an implicit nonlinear "black-box" relationship. Consequently, the model preserves the physical connection between hydration kinetics and strength development while providing greater flexibility than conventional maturity approaches based on a single apparent activation energy. Backpropagation neural networks require that all training targets be normalized within the range 0–1, as the output neurons are constrained to this interval. The software automatically performs data normalization, scaling all input data and training targets to the range 0.15 – 0.85. The network outputs are then automatically rescaled to the appropriate physical range. The ranges of variation of the individual input factors are presented in Table 2.

The comparison between measured strengths and fc values determined using the ANN-fc network was presented in Figure 6. The accuracy of the estimation for both the training and testing datasets was presented in Table 3.

After several trials, a 5-[7-4]-1 network configuration was established, as shown in Figure 4. Figure 5 shows a comparison between the measured compressive strength and network outputs

Application of the developed ANN-fc network for predicting compressive strength of mortar

A practical procedure for applying the ANN-fc model to predict mortar compressive strength as a function of curing temperature, curing time, and water-to-cement ratio (W/C) was presented in [25]. A schematic representation of this procedure is shown below. The procedure to determine *fc* is performed iteratively, as illustrated in the conceptual diagram (Figure 6):

- Calculations are performed for a fixed time step *dt*.
- Within the interval *dt* at a given temperature, the strength increment is *dYi* (MPa).
- After time $t = n \times dt$, the strength level is *Y* at the current temperature *T1*.

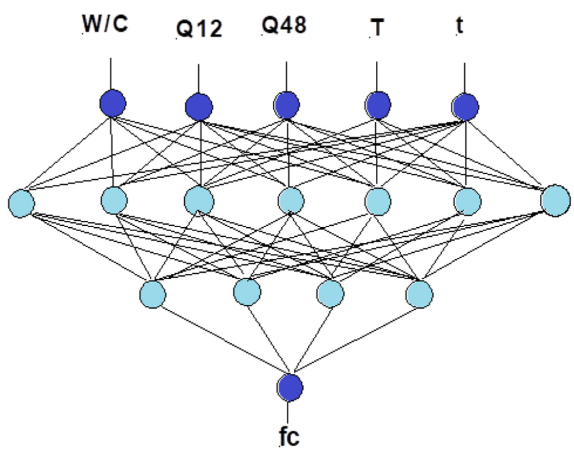

Figure 4. Structural diagram illustrating the four-layer architecture of the "ANN-fc" model

Table 2. Information on the range of variability for each of input factors

Input/Output	Unit	Label	Min	Max
W/C	-	X1	0.40	0.50
Q12	J/g	X2	46	111
Q48	J/g	X3	191	302
T	°C	X4	5	35
t – time	days	X5	1	56
fc – compressive strength	MPa	Y1	3.8	80.5

Table 3. Estimation of ANN-fc model errors

Parameter	Number of datasets	Max. error	RMS error	Correlation
Training set	173	6.03	0.0181	0.994
Test set	20	5.30	0.0137	0.956

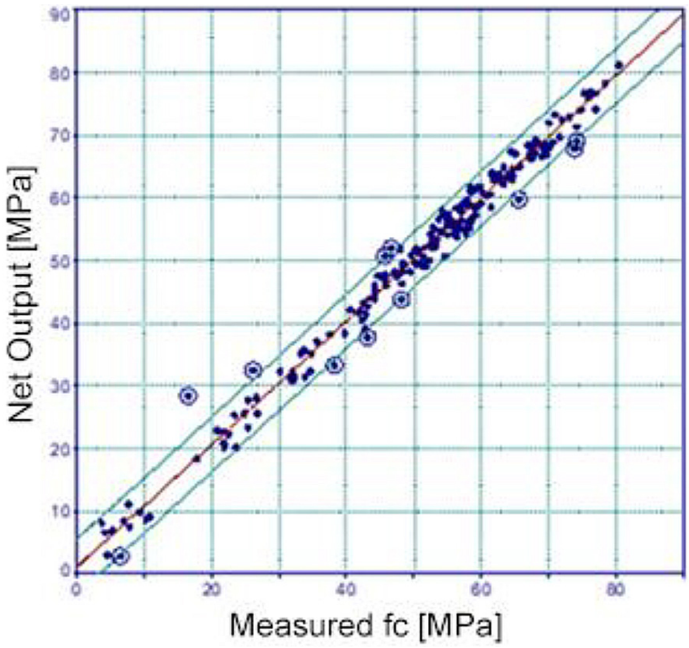

Figure 5. Comparison of measured compressive strength (f_c) with values predicted by the ANN model

- If the temperature changes to *T2* in the next time step, the time at which the strength level *Y* is reached at this temperature must be calculated, along with the strength increment *dY2*.
- In subsequent time steps, further strength increments *dYi* are calculated.
- The value of the increase in strength with changing temperature cannot be negative $dY \geq 0$.
- The final strength *Y* after a certain time *t* is the sum of the individual increments *dYi*, as shown in the lower right corner of the diagram.
- The process is repeated until the final time is reached.

A simple calculation program was prepared in Matlab [25] to perform the calculations. Initially, input data characterized the cement, such

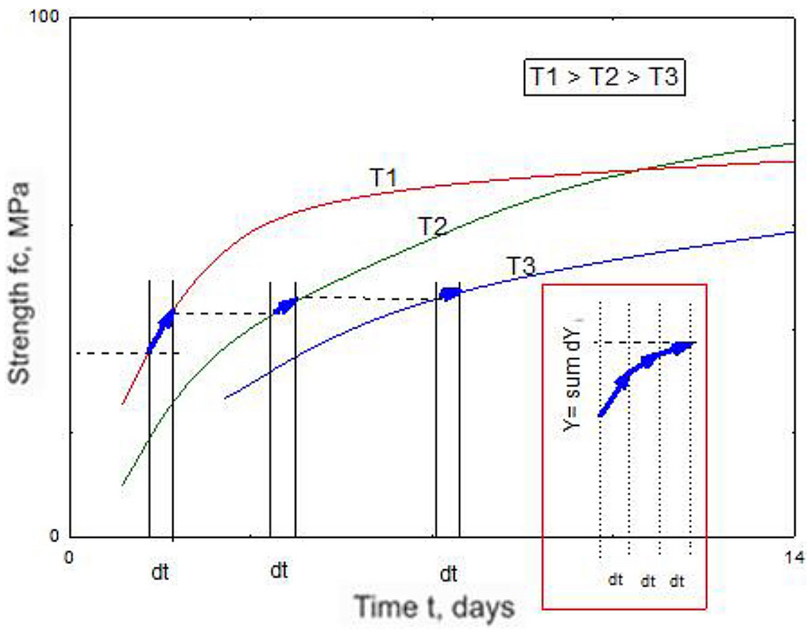

Figure 6. Procedure presented in [25]: compressive strength *fc* is calculated as the sum of strength increments in successive time steps, accounting for changes in curing temperature

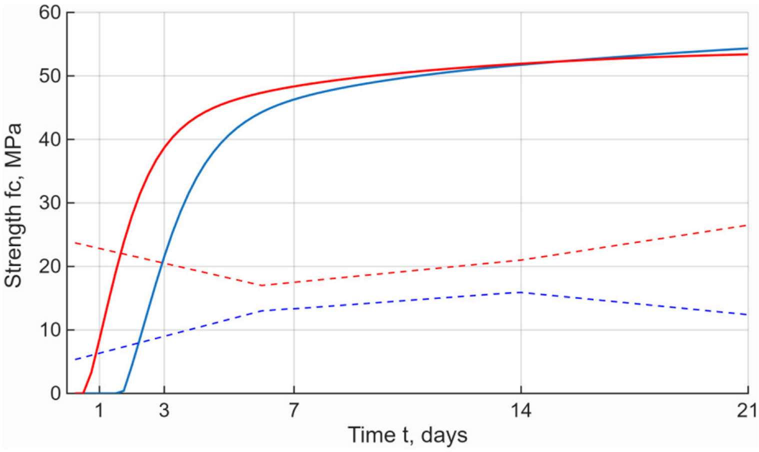

Figure 7. Development of compressive strength (fc) during curing at variable temperatures

as the heat of hydration (Q12 and Q48) and water-to-cement ratio (W/C).

Next, a data file (saved as an Excel spreadsheet) containing information on the mortar temperature history (T) during curing time (t) was uploaded. Based on these data, the MATLAB program calculated the compressive strength value (fc) using the developed ANN model. The obtained results were then used to generate the plots illustrating the development of mortar compressive strength (fc) during curing under varying temperature conditions. Examples showing the evolution of strength of the mortar made with cement C for two different temperature profiles, T1 and T2, were presented in Figure 7.

CONCLUSIONS

This study proposed a novel approach for establishing the relationship between compressive strength development and temperature history based on experimental investigations of OPC mortars. The results confirmed that compressive strength can be reliably estimated using hydration heat measurements obtained from calorimetric analysis. An ANN model was developed to describe the complex relationships between hydration characteristics, curing conditions, and strength development.

The study also demonstrated that, for a given cement, the cumulative heat released during hydration is largely independent of the water-to-cement ratio within the investigated range of 0.40–0.50. This finding enables the development of predictive models applicable to a broader range of concrete and mortar mixtures. Furthermore, the proposed methodology provides a mathematical framework that eliminates the need to determine the apparent activation energy, which is a key requirement of conventional maturity methods.

From a practical perspective, the proposed approach significantly reduces the time required to characterize a cement for strength prediction purposes, as the necessary calorimetric data can be obtained within approximately three days. Consequently, the method offers a simpler and more efficient alternative for predicting strength development under varying curing conditions while maintaining a strong physical connection to the hydration process.

The objective of this study was not to demonstrate higher prediction accuracy than the Hansen–Pedersen model, but to eliminate the experimentally demanding determination of activation energy while maintaining high prediction accuracy.

A limitation of the present study is that the ANN model was validated using randomly selected records from the available dataset, rather than cement types excluded from the training process. Therefore, the predictive capability of the model for previously unseen cement types has not yet been fully verified. Future research should include a larger database covering a wider range of cement compositions and hydration characteristics to enable more rigorous validation of model robustness and generalization capability.

REFERENCES

1. Hansen F.P., Pedersen E.J. Måleinstrument til kontrol af betons haerdning. J. Nord. Concr. Fed. 1977;1:21–25 (in Swedish).

2. Saadoon T., Gomez-Meijide B., Garcia A. New predictive methodology for the apparent activation energy and strength of conventional and rapid hardening concretes. Cem. Concr. Compos. 2021;115:103842. https://doi.org/10.1016/j.cemconcomp.2020.103842
3. ASTM International. ASTM C1074-11. Standard Practice for Estimating Concrete Strength by the Maturity Method. West Conshohocken, PA; 2011.
4. RILEM TC119-TCE. Avoidance of thermal cracking in concrete at early ages. Mater. Struct. 1997;30:451–464.
5. Kaszyńska M. Early age properties of high-strength/high-performance concrete. Cem. Concr. Compos. 2002;24(2):253–261. https://doi.org/10.1016/S0958-9465(01)00014-2
6. Lachemi M., Hossain K.M.A., Anagnostopoulos C., Sabouni A.R. Application of maturity method to slipforming operations: performance validation. Cem. Concr. Compos. 2007;29(4):290–299. https://doi.org/10.1016/j.cemconcomp.2006.12.001
7. Chanvillard G., D'Aloia L. Concrete strength estimation at early ages: modification of the method of equivalent age. ACI Mater. J. 1997;94(6):520–530.
8. Kada-Benameur H., Wirquin E., Duthoit B. Determination of apparent activation energy of concrete by isothermal calorimetry. Cem. Concr. Res. 2000;30(2):301–305. https://doi.org/10.1016/S0008-8846(99)00250-1
9. Jonasson J.E., Groth P., Hedlund H. Thermal cracking in concrete at early ages. In: Proceedings of the International Symposium on Thermal Cracking in Concrete at Early Ages; Munich; 1994. p. 45–52.
10. Carino N.J., Tank R.C. Maturity functions for concretes made with various cements and admixtures. ACI Mater. J. 1992;89(2):188–196.
11. Kurdowski W., Pichniarczyk P. Problems with the Arrhenius equation in the evaluation of concrete maturity. Cem. Lime Concr. 2016;21:149–156.
12. D'Aloia L., Chanvillard G. Determination of the apparent activation energy of concrete Ea: numerical simulations of the heat of hydration of cement. Cem. Concr. Res. 2002;32(8):1277–1289. https://doi.org/10.1016/S0008-8846(02)00791-3
13. Kuryłowicz-Cudowska A. Correlation between compressive strength and heat of hydration of cement mortars with siliceous fly ash. Minerals. 2022;12(11):1471. https://doi.org/10.3390/min12111471
14. Wirquin E., Broda M., Duthoit B. Determination of the apparent activation energy of concrete by calorimetric and mechanical means: influence of a superplasticizer. Cem. Concr. Res. 2002;32(8):1207–1213. https://doi.org/10.1016/S0008-8846(02)00737-8
15. Venuat M. Relation entre la chaleur d'hydratation et la résistance des mortiers. Rev. Mater. Constr. 1961.
16. Bobrowicz J. Relation between cement compressive strength and the amount of hydration heat evolved at low temperatures. Build. Res. Inst. 2005;3:1–14 (in Polish).
17. Ge Z., Wang K., Sandberg P., Ruiz J.M. Characterization and performance prediction of cement-based materials using a simple isothermal calorimeter. J. Adv. Concr. Technol. 2009;7(1):1–12. https://doi.org/10.3151/jact.7.1
18. Bentz D.P., Barrett T.J., De La Varga I., Weiss W.J. Relating compressive strength to heat release in mortars. Adv. Civ. Eng. Mater. 2012;1(1):1–14. https://doi.org/10.1520/ACEM20120006
19. Baran T., Pichniarczyk P. Correlation factor between heat of hydration and compressive strength of common cement. Constr. Build. Mater. 2017;150:321–332. https://doi.org/10.1016/j.conbuildmat.2017.05.170
20. Beskopylny A.N., Hematibahar M., Kharun M., Stel'makh S.A., Shcherban E.M., Ananova O. Predictive modeling of CSH formation in cement materials based on SEM and EDS analysis. Civ. Eng. J. 2025;11(6):2460–2486. https://doi.org/10.28991/CEJ-2025-011-06-017
21. Boubekeur T., Salhi M., Ezziane K., Kadri E.H. Effect of elevated temperature on the hydration heat and mechanical properties of blended cement mortars. J. Mater. Eng. Struct. 2021;8(3):341–356.
22. Rizal N.S., Arifi E., Mufarida N.A. High initial concrete compressive strength with variations of superplasticizer and silica fume additions. Civ. Eng. J. 2025;11(1):107–119. https://doi.org/10.28991/CEJ-2025-011-01-07
23. Solomon A., Ratajczak M. An assessment of the carbon footprint of concrete mixtures in relation to early strength development, evaluated using various maturity models. Adv. Sci. Technol. Res. J. 2025;19(4):171–182. https://doi.org/10.12913/22998624/200275
24. Safran M., Said I., Abuanzeh N., Baarimah A.O., Abu Saleh S., Al-Zghoul T.M., Mushtaha A.W., Alawag A.M. Impact of green building strategies on environmental, economic, and social outcomes in construction. HighTech Innov. J. 2025;6(4). https://doi.org/10.28991/HIJ-2025-06-04-019
25. Wawrzeńczyk J. A new approach for predicting strength based on temperature-time history using two-parameter maturity ANN models. Materials. 2024;17(24):6157. https://doi.org/10.3390/ma17246157
26. MathWorks. MATLAB. Version R2025a. Natick (MA): MathWorks; 2025.