Predicting temperature drop rate of mass concrete during an initial cooling period using genetic programming

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Abstract. Thermal cracking on concrete dams depends upon the rate at which the concrete is cooled (temperature drop rate per day) within an initial cooling period during the construction phase. Thus, in order to control the thermal cracking of such structure, temperature development due to heat of hydration of cement should be dropped at suitable rate. In this study, an attempt have been made to formulate the relation between cooling rate of mass concrete with passage of time (age of concrete) and water cooling parameters: flow rate and inlet temperature of cooling water. Data measured at summer season (April- August from 2009 to 2012) from recently constructed high concrete dam were used to derive a prediction model with the help of Genetic Programming (GP) software “Eureqa”. Coefficient of Determination (R) and Mean Square Error (MSE) were used to evaluate the performance of the model. The value of R and MSE is 0.8855 and 0.002961 respectively. Sensitivity analysis was performed to evaluate the relative impact on the target parameter due to input parameters. Further, testing the proposed model with an independent dataset those not included during analysis, results obtained from the proposed GP model are close enough to the real field data.

Keywords: Mass concrete; Eureqa; prediction; genetic programming; temperature drop rate

1. Introduction
Mass concrete plays an important role in modern construction, especially in hydraulic and hydroelectric construction. For example, in China more than 10 million m³ mass concrete are poured every year in hydraulic and hydroelectric engineering. Besides, the structure of harbor engineering and foundations of heavy machines are often built with mass concrete. In such structures, heat of hydration of cement increases the internal temperature of concrete due to its exothermic chemical reaction and induces thermal gap induces between inside and outside of structure leading to tensile stress which ultimately results in thermal cracking of such structures almost at early age [1, 2]. In order to reduce/control the maximum internal temperature of concrete and to fasten the cooling process, chilled water is circulated through the interconnected cooling pipes embedded into the concrete during construction [3, 4]. This technique was first studied in early 1930’s by USA Bureau of reclamation in the design of Hoover Dam [5].

Thermal cracking in mass concrete structure at early age depends upon the rate of which the concrete is cooled (temperature drop rate per day, \(\Delta T^{\circ}\text{C/day}\)) at an initial cooling period. Thus, temperature of mass concrete should be dropped at suitable rate to control the cracking of mass concrete during the construction phase. There are lots of factors to be considered to prevent thermal induced cracking of mass concrete at an early age. Reducing the maximum internal temperature of concrete, adjustment of suitable combination of water cooling parameters: flow rate \(q_w\), inlet temperature of cooling water \(T_w\)
and controlling the rate at which the concrete cools (temperature drop rate), are some of them. Further, \( \Delta t \) depends upon many parameters like, thermal properties of concrete, spacing of pipe, \( q_w \), \( T_w \), age of concrete \( (A_c) \), construction season (Summer or Winter) and so on. Relationships between these parameters are non-linear in pattern, complicated and not well understood yet. Due to the lack of simple and practical formula, in recent construction of concrete dams, \( T_w \) and \( q_w \) are adjusted based on numerical simulation and engineering experience to control the temperature of concrete.

A number of researches emphasis on controlling temperature of mass concrete using numerical simulation [6-9]. Further, most recent researches conducted for determining the temperature field of concrete dam at construction phase are based on Finite Element Methods (FEM) are [10, 11], composite element method [12] and heat fluid coupling method [13]. Thermal crack analysis during pipe cooling was simulated using Particle Flow Code method [14]. However, very few researches have investigated the cooling rate of mass concrete during an initial cooling period at the construction phase of massive concrete structures. EM 1110-2-2201(1994) suggests not to drop the temperature of mass concrete during more than \( \frac{1}{2} \) to 1 \(^\circ\)F per day during an initial cooling period [15]. ACI 207.4R (1993) reported the cooling rates, in degrees per day, for latter period should be lower than the permitted during initial periods because of the higher modulus of the elasticity at later ages [16]. Also this report suggests, after the concrete reached its peak temperature, cooling should be continued for a period of 1 to 2 weeks at a rate such that the concrete temperature drop generally not exceed 1 \(^\circ\)F (0.6 \(^\circ\)C) per day (the maximum rate that does not exceed the early age tensile strain and creep). For some condition, cooling rate of 2 \(^\circ\)F (1 \(^\circ\)C) per day can be accepted for a short period of time [16]. Nannan Shi et al. (2014) investigated; lower cooling rates can reduce the probability of concrete cracking [17]. Further, temperature control of mass concrete during the construction phase of concrete dams seems more complicated due to the varying properties of concrete with the passage of time \( (A_c) \). Moreover, construction time plays an important role in any project; thus, in order to complete the project within the time frame, it is often needed to pour the concrete in a high temperature summer seasons. If an effective temperature control measure is not taken for concrete poured at higher summer season undesirable and unavoidable cracks will be the result [18].

Therefore, in order to prevent the cracks during the construction phase of concrete dams, it is very important to understand the relationship between the parameters involved in the process. In the present study, attempts have been made to develop a robust prediction model to predict \( \Delta t \) at an initial cooling period during the construction phase of concrete dams. Data measured at summer construction season (April- August from 2009 to 2012) are used to formulate the relationship. For this, \( T_w \), coefficient of pipe cooling \( (p_i) \) which is dependent \( q_w \) and \( A_c \) are taken as the input variables whereas values of \( \Delta t \) is taken as the target variable.

2. Materials

2.1. Data Source

In order to formulate the relationship to determine \( \Delta t \), data were taken from the project named “Xiluodu high concrete arch dam (285.5 m high) which was recently constructed and located in the lower reach of the Jingsha River, Yunnan Province, in southwest China [19]. During the construction of the project, an optical fiber (shown in Figure 1) was embedded in concrete to monitor the temperature of concrete. Data’s from monolith 15 and monolith 16 during the construction at summer season (April- August from 2009 to 2012) were chosen. Three types of concrete namely Concrete Type A, Concrete Type B and Concrete Type C were used while constructing the dam. In this study, Concrete Type A was used for formulating and verification of the developed model. Thermal properties of concrete (Concrete Type A) as: thermal conductivity, diffusivity, specific heat and density and water cooling data as: diameter of water cooling pipe, conductivity of pipe, length of cooling pipe and spacing of cooling pipe \( (H: V) \) as 1.5m*1.5m and lift height \( (1.5 \text{ m and } 3\text{ m}) \) were taken as the real situation of the research project. Thermal properties of concrete are listed in Table 1.
2.2. Data Analysis and Preparation

Concrete gain its peak temperature after a few days to week of placement. After the concrete reaches its maximum/initial value, dropping of temperature from this value to the target value (design value) at an early age (around 30 days) is fully controlled by circulating water through the cooling pipes embedded in the concrete during construction. The time period that takes dropping the maximum/initial temperature to target temperature at early stage is known as initial cooling stage/period. The overall cooling process used during the construction phase is shown in Figure 2.

To develop the prediction model for temperature drop rate, concrete temperature data (recorded from optical fiber at different time interval within a day for each lift taken in this study) and water cooling data (measured at almost the same time of concrete temperature measurement) within initial cooling stage are utilized in this study. Concrete temperature data are taken at the time lag of almost 12 - 24 hours between two consecutive days. For some cases, concrete temperature data of latter days are greater than previous days, in such cases, the value of Δt is negative and those negative values of Δt has been removed during developing the model. The set of data for Δt before building the model is prepared as follows:

\[ \Delta t_i = t_{i-1} - t_i \]  

(1)
Where,
\[
\Delta t = \Delta t_i = \text{temperature difference of mass concrete of } [(i-1^{\text{th}}) - i^{\text{th}}] \text{ day in } ^{\circ}\text{C/day}
\]
\[
t_{i-1} = \text{temperature of concrete at } i^{\text{th}-1} \text{ day in } ^{\circ}\text{C}
\]
\[
t_i = \text{temperature of concrete at } i^{\text{th}} \text{ day in } ^{\circ}\text{C}
\]
i=2, n: n is total numbers of days at initial cooling period for individual lifts.

The relation given in equation (1) is demonstrated by the following example:
Suppose, for lift number 3, initial cooling period is 21 days ranging from date 2009/4/1: 8:00 PM to 2009/4/22: 8:00 PM. Concrete temperature at date 2009/4/1: 8:00 PM and 2009/4/2: 8:00PM is 25.6 \(^{\circ}\text{C}\) and 25.2 \(^{\circ}\text{C}\) respectively, then the value of \(\Delta t\) for day 2009/4/2: 8:00 PM is 25.6 - 25.2 = 0.4 \(^{\circ}\text{C/}\text{day}\). For preceding days up to initial cooling period, the same concept applies. In this example i =2, n, 2 denotes the latter day 2009/4/2: 8:00 PM and n denotes the last date of initial cooling period, i.e., 2009/4/22: 8:00 PM. Similarly, for other lifts \(\Delta t\) is calculated in the same manner.

Further, coefficient of pipe cooling, \(p_1\) (which depends upon \(q_w\)) can be derived from the following relationship, Zhu [20]. The rate of flow of cooling water is taken almost at the same time of calculating \(\Delta t\).

\[
p_1 = k_i (ga / D^2)^{s}
\]

(2)

Where,
\[
k_i = 2.08 - 1.17 \xi + 0.256 \xi^2
\]

(3)

\[
s = 0.971 + 0.1485 \xi - 0.0445 \xi^2
\]

(4)

\[
\xi = \frac{\lambda L}{c_w \rho_w q_w}
\]

(5)

\[
g = 1.67 \exp\{-0.0628[B \left( \frac{c}{r_0} \right)^n - 20]^{0.48}\}
\]

(6)

In which, \(g\) is a coefficient to consider the influence of \(b/c\) and the material of pipe

\[
b = 0.5836 \sqrt{(S1*S2)}
\]

(7)

Where, \(a\) is the thermal diffusivity of concrete (m\(^2\)/day); \(b\) is the outer radius of concrete cylinder (m); \(c\) is the inner radius of concrete cylinder (m); \(c_w\) is the specific heat of cooling water (kJ/Kg \(^{\circ}\text{C}\)); CD is the Construction Date; D is the diameter of concrete cylinder (m); \(L\) is the length of pipe (m); \(r_0\) is the inner radius of non-metal cooling pipe (m); \(S_1\) is the horizontal spacing between cooling pipes (m); \(S_2\) is the vertical spacing between cooling pipes; \(\lambda\) is the coefficient of thermal conductivity of concrete (kJ/m h \(^{\circ}\text{C}\)); \(\lambda_1\) is the coefficient of thermal conductivity of non-metal cooling pipe (kJ/m h \(^{\circ}\text{C}\)); \(\rho_w\) is the density of cooling water (kg/m\(^3\)); and \(\eta = \lambda / \lambda_1\)

Calculation for \(A_c\) is demonstrated by the following example:
Suppose, for lift number 3, initial cooling period is 21 days ranging from date 2009/4/1: 8:00PM to 2009/4/22: 8:00PM. If the date of construction of lift 3 is 2009/3/25: 5:45: AM, then the age of concrete up to date 2009/4/1: 8:00PM is 2009/4/1:8:00PM - 2009/3/25: 5:45: AM = 7.59375 days. Likewise, the age of concrete for each day up to initial cooling period of lift 3 can be calculated for the exact time of calculating \(\Delta t\). Likewise, for other lifts, age of concrete is calculated on the same principle. To formulate the GP model, descriptive statistics of the input data are tabulated in Table 2.

| Rank | \(p_1\) | \(T_w\) \(^{\circ}\text{C}\) | \(A_c\) (days) | \(\Delta t\) \(^{\circ}\text{C/day}\) |
|------|--------|-----------------|----------------|----------------|
|      |        |                 |                |                |

Table 2: Descriptive statistics of input data
Mean | 0.0358513 | 11.95405 | 18.32993 | 0.221986  
Median | 0.035000 | 14.00000 | 17.71002 | 0.21150  
STDEV* | 0.006295 | 2.79579 | 6.68767 | 0.11293  
Variance | 3.9635E-05 | 7.81649 | 44.72497 | 0.01275  
Maximum | 0.046000 | 15.30000 | 31.11875 | 0.46700  
Minimum | 0.023000 | 6.00000 | 6.70104 | 0.00900  

* = Standard Deviation

3. Methods

3.1. Genetic Programming, Eureqa and Automated Solution Seeking

Recently, soft computing technique (like artificial neural networks (ANNs) and fuzzy neural network systems), which are considered as strong machine learning techniques have been gaining popularity for solving complex problems in the field of civil engineering [21-23]. Genetic Programming (GP), which was first introduced by John Koza in (1992) [24] is another branch of machine learning method, which automatically generates computer programs based on the rule Darwinian natural selection and biologically inspired operations to solve the user-defined task. Genetic programming (as an extension of genetic algorithm) evolves a series of computer programs (semi complex mathematical equations) instead of data to solve a complex non-linear problem and can be suitable for real problem [25]. GP uses an evolutionary algorithm in order to optimize the computer programs through expression tree according to fitness function.

Eureqa® software package sometimes can be called as robot scientist, developed by Dr. Hod Lipson [26] is fairly new, publicly available product from Cornell Creative Machines Lab [27] is a symbolic regression tool for automated numerical regression methods, optimization, detecting equations and hidden mathematical relationships in raw data and is based on GP. Eureqa has been applied for solving some problems in civil engineering field [25, 28-29]. Correlation coefficient (R) and Mean Square Error (MSE) were used to evaluate the performance of each model. In Eureqa, each variable values can be assigned to single rows and searches are specified by writing a search function. A solution fit plot against predicted and actual data, list of candidate function ranked by fitness (error/complexity), a plot of solution respective to their error size; residual error plot and a plot of different fitting statistics of the generated solutions can be obtained as output in Eureqa [28].

3.2. Development of model using GP

To get the suitable GP model, basic arithmetic operators (+, -, *, /), trigonometric operator (sin, cos) and some basic exponential functions (exponential, natural logarithm, square root, factorial and power) were utilized in this study. Un-normalized data of the individual variables has been normalized during building the model. The GP software identified un-normalized data of the individual variables. And those identified un-normalized data’s from GP software for each variables is normalized by algorithm “subtracted by mean and divided by standard deviation”. 145 numbers of rows of each input and an output variable were gathered. 51 numbers of data were chosen for training, 24 numbers of data were chosen for validation and 70 numbers of data were chosen for testing of the proposed model (chosen randomly). Following function is used to obtain the hidden relationship between Δt and the influencing variables:

\[ \Delta t = f (p_1, T_w, A_c) \]  

(8)

4. Results and Discussions
4.1. GP-Based Formulation for $\Delta t$

The GP approach was employed in this study to predict $\Delta t$ of mass concrete at an initial cooling period during the construction phase of concrete dam. Final model is established by comparing the output from the developed model with the experimental data. The best two models evaluated from GP are shown in Table 3. The value of R close to 1 and low value of MSE indicates the data were more fitted. The value of R given in Table 3 is for validation dataset. According to the performance evaluation criteria, model no 1 is the comprising model among others.

Table 3: Different GP Based Prediction Models

| Rank | MSE     | R       | Expressions                                      |
|------|---------|---------|--------------------------------------------------|
| 1    | 0.00296 | 0.8855  | $\Delta t = \frac{0.755 + 160p_i}{5.73 + A_i + 1.24T_w + \sin(2.08A_i)(0.00101A_i^3 - 1.25) + 0.363A_i\sin(2.53\sin(4.76e4 A_i)) + 160p_i}$ |
| 2    | 0.00297 | 0.8848  | $\Delta t = \frac{0.63 + 160p_i}{5.73 + A_i + 1.19T_w + \sin(2.08A_i)(0.000999A_i^3 - 1.25) + 0.358A_i\sin(2.54\sin(4.76e4 A_i)) + 160p_i}$ |

Due to the lack of previously developed rational models to predict $\Delta t$ at an initial cooling period during the construction phase of concrete dam, it is not possible to conduct a comparative study of the results obtained from this study to those of previous studies. According to Smith [30], when the model gives $|R|>0.8$, a strong correlation exists between the predicted and measured values. As can be seen from Table 3, the entire model has $|R|>0.8$, which reveals that the proposed model has a good predictive ability.

4.2. Performance of the Model

In order to determine the prediction capability of the proposed model, comparisons were made between the predicted values of $\Delta t$ from GP model with real $\Delta t$ that were not included during an analysis by plotting the graph as shown in Figure 3.

It is obvious from Figure 3, during testing phase the predicted and real $\Delta t$ were strongly correlated with a linear relationship with $R^2/R$ of 0.7202/0.8486 from the proposed model. Beside validation, performance of the derived model is verified by comparing the prediction output from the derived model with the real field data those were not included during the analysis as shown in Figure 4. Comparison (shown in Figure 4) was made between the predicted $\Delta t$ and real $\Delta t$ (data available from the same research project having different value of $qw$ and $T_w$ per day). The calculated results from proposed model shows a pretty good agreement with the real field data for summer month from April to August for different year which indicates that the proposed model is obvious.
Figure 3: Comparison between real $\Delta t$ and predicted $\Delta t$ during the testing phase

Figure 4: Comparative study of result from GP-model with real field data: (a) Lift 74 of monolith 15 (CD: 2012/4/17), (b) Lift 5 of monolith 15 (CD: 2009/5/9), (c) Lift 72 of monolith 16 (CD: 2012/6/16), (d) Lift 85 of monolith 15 (CD: 2012/8/30)

Note: Green and Grey line used in Figure 4b - Figure 4d is the same used in Figure 4a
4.3. Sensitivity Analysis

Sensitivity analysis was performed to evaluate the relative impact on the target variables due to input variables. For a given model in the form \( z = f(x, y, \ldots) \), sensitivity is expressed as follows:

\[
Sensitivity = \frac{\sigma(x)}{\sigma(z)} \frac{\partial z}{\partial x}
\]

(9)

Where: \( \partial \) = partial derivate operator, \( \sigma(x) \) = standard deviation of \( x \) in the input data, \( \sigma(z) \) = standard deviation of \( z \) [27].

The term percent positive is defined as the percent of data in which the partial derivative of the target value with respect to the \( i^{th} \) input is greater than zero. This number shows the possibility that increasing the specified input parameter would increase the target value in the model and the same concept applies for a negative value of the aforementioned derivative term known as percent negative. Further, positive magnitude is the number that denotes generally how big the positive impact is, when increases in this variable lead to increases in the target variable and same concept applies for a negative magnitude [27]. A summary of sensitivity, percent positive, positive magnitude, percent negative and negative magnitude values for the GP-based model is shown in Table 4.

Table 4: Sensitivity analysis of the GP model

| Input Variable* | Sensitivity | Percent Positive | Positive Magnitude | Percent Negative | Negative Magnitude |
|-----------------|-------------|------------------|--------------------|-----------------|--------------------|
| \( p_1 \)       | 0.37518     | 100              | 0.37518            | 0               | 0                  |
| \( T_w \)       | 0.28847     | 0                | 0                  | 100             | 0.28847            |
| \( A_c \)       | 36.536      | 41               | 38.882             | 59              | 34.898             |

*As defined in expressions in Table 3.

Sensitivity analysis result shown in Table 4 indicates, input parameters \( p_1 \) and \( T_w \) are possess high positive and negative impact to the target parameter respectively, whereas parameter \( A_c \) has percent negative of 59% ≈ 60%, thus it is supposed to have negative impact on the target parameter.

The proposed GP model developed in this study was formulated from the data available from single dam constructed at summer season from April to August. Therefore, the model derived from this study can be used in preliminary design stages rather than in final decision making. Although, the derived model holds good agreement within the range of data given in Table 2, the model should be used carefully for prediction outside the range of parameter taken in this study. This proposed model could be improved to make a precise prediction over a wider range considering different pipe spacing and initial cooling duration, if the data could be made available from other similar projects. This research is expected to be helpful where high concrete dams are anticipated to build in near future.

5. Conclusion

The GP approach was employed in this study for predicting \( \Delta t \) of mass concrete at an initial cooling period during the construction phase of high concrete dam. This model will be capable to sort out the complication of adjusting the water cooling parameters \( (q_w \text{ and } T_w) \) during the construction phase of concrete dam in order to drop the maximum temperature of concrete. The developed model has the \( R \) value of 0.8855 (which is greater than suggested good fit \( |R| > 0.8 \)) and significantly low MSE (0.002961), which indicates the proposed model have good predictive ability. Beside validation, testing the model applicability with an independent dataset (those not included during analysis), proposed model is capable of generalizing the input and output variables with reasonably good predictions. Sensitivity analysis results clarifies that input parameters: \( p_1 \) possess positive impact and \( T_w \) is sensitive in-terms of negative impact on the target variable whereas parameter \( A_c \) has percent negative of 59% ≈ 60% which is supposed to be have negative impact on the target variable. Using the derived model, required \( \Delta t \)
during initial cooling period at construction phase of concrete dam can be easily calculated using the variable taken in this study, which will be beneficial in terms of time saving for sophisticated laboratory experiment.

**Conflicts of Interest**
The authors declare no conflict of interests regarding the publication of this paper.

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