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APPLICATION OF SOFT COMPUTING TECHNIQUES FOR PREDICTING COOLING TIME REQUIRED DROPPING INITIAL TEMPERATURE OF MASS CONCRETE.

Santosh Bhattarai[1], Yihong Zhou[1], Chunju Zhao[1] and Huawei Zhou[2]*

1. College of Hydraulic and Environmental Engineering, China Three Gorges University,Yichang 443002,P.R. China

2. School of Water Resources and Hydroelectric Engineering, Wuhan University, Wuhan , P.R. China

** Corresponding author: Contact no+86-13972605689, E-mail address: zyhwhu2003@163.com*

ABSTRACT

Minimizing the thermal cracks in mass concrete at an early age can be achieved by removing the hydration heat as quickly as possible within initial cooling period before the next lift is placed. Recognizing the time needed to remove hydration heat within initial cooling period helps to take an effective and efficient decision on temperature control plan in advance. Thermal properties of concrete, water cooling parameters and construction parameter are the most influencing factors involved in the process and the relationship between these parameters are non-linear in a pattern, complicated and not understood well. Some attempts had been made to understand and formulate the relationship taking account of thermal properties of concrete and cooling water parameters. Thus, in this study, an effort have been made to formulate the relationship for the same taking account of thermal properties of concrete, water cooling parameters and construction parameter, with the help of two soft computing techniques namely: Genetic programming (GP) software "Eureqa" and Artificial Neural Network (ANN). Relationships were developed from the data available from recently constructed high concrete double curvature arch dam. The value of R for the relationship between the predicted and real cooling time from GP and ANN model is 0.8822 and 0.9146 respectively. Relative impact on target parameter due to input parameters was evaluated through sensitivity analysis and the results reveal that, construction parameter influence the target parameter significantly. Furthermore, during the testing phase of proposed models with an independent set of data, the absolute and relative errors were significantly low, which indicates the prediction power of the employed soft computing techniques deemed satisfactory as compared to the measured data.

KEYWORDS

mass concrete, temperature control, cooling, placing time, artificial neural network, genetic programming

INTRODUCTION

Mass concrete plays an important role in modern construction, especially in hydraulic and hydroelectric construction. For example, in China more than 10 million m^3 of 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 massive concrete structures like concrete dams, temperature control and thermal crack prevention during construction is very important and challenging task. The problems arise from the thermal properties of concrete, which vary with time as the concrete hardens as well as temperature and multiple factors affecting the temperature rise curve.

Pipe cooling, which was first studied in early 1930's by USA Bureau of reclamation in the design of Hoover Dam [1], is regarded as one of the effective method to control the thermal cracking in a mass concrete structure during the construction phase. Controlling the temperature development in a massive concrete structure is realized by flowing chilled water through the interconnected pipe networks embedded into the concrete during construction [2, 3]. However, pipe cooling is also a double-edged sword, which could cause damage the concrete in the case of improper control. In modern water-conservancy construction, to minimize the thermal cracks at construction phase, pipe cooling is mainly conducted in three phase namely: initial cooling period, mid-term cooling period and late term cooling period.

Especially, for large concrete structures which are made sequentially in a series of blocks of 1.5m -3.0m, it is therefore necessary to remove as much of heat of hydration as possible during initial cooling period taking the full benefit of low modulus of elasticity of concrete at an early age to minimize the thermal cracks. As, construction time is usually an important consideration, it is essential to carry out the heat removal as quickly as possible before the next lift is placed. According to ACI 207.4R (1993), duration of an initial cooling period can be as short as several days or as long as one month but one or more additional cooling periods can be added if the increase in concrete temperature is significant after an early/initial cooling [4]. EM 1110-2-2201(1994) suggests not to extend an initial cooling period more than 15 to 30 days to control the peak temperature [5]. During initial cooling period at construction phase of concrete dams, the water cooling flow (q_w) and inlet temperature of water (T_w) is adjusted based on the numerical calculation and engineering experience to remove the hydration heat. Recently, due to the lack of simple and practical relationship between the parameters involved in controlling hydration heat (initial temperature of concrete, T_0) during the initial cooling duration, temperature control process seems more complicated.

Therefore, understanding the relationship between the cooling time (*CT*) required to drop a T_0 to the target temperature (T_t) or to the temperature at the end of an initial cooling period (T_e) during initial cooling period with cooling water parameters as: (T_w, q_w, spacing of cooling pipe and diameter of cooling pipe), thermal properties of concrete and construction parameter (construction time lag between successive lifts, P_f) helps to take an efficient and effective decision on temperature control plan in advance. Relationships between these parameters are non-linear in pattern, complicated and not well understood yet. Some attempts had been made to understand and formulate the relationship taking account of thermal properties of concrete and water cooling parameters. Zhu (2014), proposed one practical formula for the calculation of the time required to drop T_0 at any interval (from T_0 to T_e or from T_0 up to T_t) within an initial cooling period at construction phase of concrete dams [6]. ACI 207.1R (1996) gives an approximation method to calculate *CT* needed for accomplishing the required temperature reduction of concrete using graphs [7]. However, parameter P_f has not been considered during formulation of relationship in previous studies.

Further, some attempts had been made by some researchers to co-relate the variation of concrete temperature with parameter P_f during the construction phase of a concrete dam. According to IS (1999) and Fairbairn, Silvoso et.al (2004), increase in the construction time period between two successive lifts allows the maximum temperature to dissipate before the next lift is placed [8, 9]. Zhu (2014) believes parameter P_f and spacing of cooling pipes greatly influence the thermal stress during an initial cooling period [6]. Wang, Liu et.al (2015) stated, the maximum temperature of concrete occurs after 5 to 7 days of P_f and the correlation between the maximum temperature and the interval length is trivial when the pouring interval is from 15 to 28 days [10]. Mentioned literatures reflect that the parameter P_f plays an important role in controlling the temperature of concrete during the construction phase.

Over the last two decades, where the non-linearity between the parameters cannot be understood logically and complex to solve analytically, soft computing tools (like ANNs, fuzzy neural network systems and GP) inspired by the human brain is gaining popularity in civil engineering. ANN method is widely used by many researchers for determining different properties of concrete [11-13] and concrete structures [14-16]. Among these soft computing techniques, GP which was first introduced by John Koza (1992) [17], is another branch of machine learning methods which automatically generates computer models based on the rule of natural genetic evolution. Due to the ability to discover the underlying data relationships and express them in semi-complex mathematical form rather than data without any assumptions on priori functional form of the solution [18 -20], different types of GP likes: gene expression programming [21, 22] and multi gene-genetic programming [16] has been utilized to derive simplified model for solving civil engineering problems. Commercial code based GP software" Eureqa" is a symbolic regression tool for detecting equations and hidden mathematical relationships in raw data [23]. There have been some scientific efforts aiming to apply Eureqa for solving some problems in civil engineering field [19, 24].

The literature review, as discussed above, reveals that no research has been undertaken with the help of GP and ANN to formulate the relationship between CT required to drop T_0 at any interval within an initial cooling period encompassing thermal properties of concrete, water cooling parameters and construction parameter. The present study is intended to formulate the relationship for the same. To formulate the relationship, the coefficient of pipe cooling (p_1), T_w in ^{0}C, Δt (temperature difference between T_0 and T_t or T_0 and T_e within an initial cooling period) in ^{0}C and P_f in days were entered as the inputs while the CT values were used as output. Developing such models will be beneficial in-terms of saving cost and time for laboratory works and helps to make an efficient and effective decision on temperature control plan in advance.

DATA SOURCE AND ANALYSIS

To achieve the objective of this research, data were taken from the project named "Xiluodu high concrete double curvature arch dam (285.5 m high and 700 m crest length)" which was recently constructed and located in the lower reach of the Jingsha River, Yunnan Province, in southwest China [25]. During the construction of the project, an optical fiber was embedded (as shown in *Fig. 1*) in four monoliths namely, 5#, 15#, 16# and 23# to monitor the temperature of concrete.

Fig. 1 - On-site Schematic layout of optical fiber

Concrete temperature data recorded from the optical fiber at different time interval within a day for every lift of each monolith and water cooling data (T_w and q_w) measured almost at the same time of concrete temperature measurement within an initial cooling period were taken in this study. Both the concrete temperature and water cooling data were then averaged for an individual day within the initial cooling period.

Further, the coefficient of pipe cooling p_1 (which is dependent on q_w) is derived from the following relationship, Zhu [6].

$$p_1 = k_1 (ga / \mathrm{D}^2)^s \tag{1}$$

Where,

$$k_1 = 2.08 - 1.17\xi + 0.256\xi^2 \tag{2}$$

$$s = 0.971 + 0.1485\xi - 0.0445\xi^2 \tag{3}$$

$$\xi = \frac{\lambda L}{c_w \rho_w q_w} \tag{4}$$

$$g = 1.67 \exp\{-0.0628[\frac{b}{c}(\frac{c}{r_0})^\eta - 20]^{0.48}\} \tag{5}$$

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

Where,

$$b = 0.5836 * \sqrt{(S_1 * S_2)} \tag{6}$$

Designation, unit and the values (taken as the real situation of the research project) of the parameters (thermal properties of concrete and water cooling pipe parameters) used in Equation 1 – Equation 6 are tabulated in *Tab. **1***.

Tab. 1 - Thermal Properties of Concrete and Water Cooling Parameters

Parameters	***Designation***	***Unit***	***Value***
Coefficient of thermal conductivity of concrete	λ	kJ/mh ^{0}C	7.28
Thermal diffusivity of concrete	a	m^2/day	0.067
Outer radius of concrete cylinder	b	m	0.875 / 0.715 / 0.584
Diameter of concrete cylinder	D =2*b	m	1.75 / 1.43 / 1.168
Coefficient of thermal conductivity of non-metal cooling pipe	λ_1	kJ/mh ^{0}C	1.6
Length of pipe	L	m	300
Outer radius of non-metal cooling pipe	c	m	0.040
Inner radius of non-metal cooling pipe	r_0	m	0.033
Density of cooling water	ρ_w	kg/m^3	1000
Specific heat of cooling water	c_w	kJ/kg ^{0}C	4.187
Horizontal and Vertical Spacing of Cooling Pipes (H:V)	S_1 * S_2	m *m	1.5m*1.5m,1.0m*1.5 m and 1.0m*1.0m
Rate of flow of cooling water	q_w	m^3/h	0.3 – 3.06
$\eta = \lambda/\lambda_1$			4.55

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108 numbers of lifts (lift height of 1.5 m and 3 m) from monoliths 15#, 16# and 23# containing 2974 rows of each input and output variables were used for building/training and validating the models. Beside validation, 45 numbers of lifts from monolith 5# containing 257 rows of each input and output variables were used for testing (checking the applicability) of the proposed models. Descriptive statistics of the input data that were used to formulate the prediction models for *CT* from GP and ANN techniques are tabulated in *Tab.* ***2***. Both the models were run (expect the variables T_0 and T_e) within the range of value given in *Tab.* ***2***. Further, q_w was taken within the minimum and maximum range 0.3m^3/h and 3.06m^3/h respectively.

Tab. 2 - Descriptive Statistics of Input Data

	Input						***Target***
Input*	p_1	$T_w\,^0C$	$T_0\,^0C$	$T_e\,^0C$	$\Delta t\,^0C$	P_f(days)	*CT* (days)
Mean	0.043	15.114	24.048	20.052	2.234	12.99	17.45
Median	0.038	15.165	24.027	20.009	1.973	11.00	15.00
STDEV*	0.011	0.852	1.737	1.269	1.531	6.29	12.24
Variance	0.000	0.726	3.017	1.610	2.343	39.58	149.81
Maximum	0.014	12.821	20.296	16.569	0.012	5.00	1.00
Minimum	0.072	18.392	28.766	25.477	8.658	36.00	65.00

*=Standard Deviation

METHODS

Eureqa and Automated Solution Seeking

Eureqa® software package, developed by Dr. Hod Lipson [26] is fairly new, publically available product from Cornell Creative Machines Lab *http://creativemachines.cornell.edu/eureqa* [23] 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. The evolution of the programs toward the best solution is controlled by an appropriate fitness functions namely: mean squared error (MSE), mean absolute error (MAE), mean relative error (MRE) and correlation coefficient (R). The best GP solution is eventually validated through the use of an independent set of data which was not introduced during a training phase. 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 [24].

Development of the empirical model using GP

Commercial code based GP software "Eureqa" was utilized for deriving the GP model. To get the suitable GP model, the basic arithmetic operators (+, -, *, /), the trigonometric operator (sin, cos) and some basic exponential functions (exponential, natural logarithm, square root, factorial and power) were utilized in this study. The four numbers of input parameters p_1, T_w, Δt *and* P_f were taken for deriving output parameter *CT*. Following function is used to obtain the hidden relationship between *CT* and the influencing variables:

$$CT = f\,(p_1,\ T_w,\ \Delta t,\ P_f) \quad (7)$$

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Dataset containing 2974 numbers of rows of each input and output variables were divided randomly into two parts (training and validation). Percentage division of dataset for formulating the GP model is listed in *Tab. **3***. According to Marref et al. (2013), the division of data's used during building the model can be altered while fulfilling two opposing criteria: (i) while deriving the model, the size of the dataset used in training should be as large as possible to account for a diversity of data and (ii) For validation of the derived model, the size of the dataset used can be as large enough to avoid for over fitting of the proposed model [27].

Development of the model using ANN

A successful application of an ANN needs a good conception of the impact of different internal parameters. For ANN architectures and training of the same, the significant internal parameters include learning rate, initial weights, learning cycle ,number of training epochs, numbers of hidden layers, numbers of neurons in each hidden layer and transfer functions for hidden layers and output layers [11]. In this study, a three-layered feed-forward network was trained with back-propagation (BP) training algorithm. Levenberg-Marquardt (LM) was utilized as a learning algorithm because of its ability to provide the numerical solution to the problem by minimizing a non-linear function quickly.

The software MATLAB (R.2014.b) was chosen among different programming languages as this software provides most efficient and flexible environment to develop an ANN [28]. A program code is written to perform the necessary computations. The same dataset used for developing GP model were utilized to construct an ANN. The input data sets were randomly divided into three parts: learning/training phase, validation phase and test phase. Percentage division of dataset used for developing the ANN model is listed in *Tab. **3***.

Tab. 3 - Division of dataset for formulating GP and ANN model

Method	Training (%)	Validation (%)	Test (%)	Testing (Checking Model Applicability)
GP	50%	50%		257 numbers of data from monolith 5#
ANN	60%	20%	20%	257 numbers of data from monolith 5#

The ANN developed in this research consists of four neuron (inputs) in an input layer and one neuron (output) in an output layer. The numbers of neurons in the hidden layer was adjusted 13 after doing many trial and errors. A non-linear hyperbolic tangent sigmoid function and linear function were used as transfer functions in hidden and an output layer respectively due to their ability to learn the complex non-linear relation between an input parameter and an output parameter [11]. Network training parameters adopted to construct an ANN model are summarized in *Tab. 4*.

Tab. 4 - Parameters used in ANN model

Parameters	ANN
Number of neurons in input layer	4
Number of hidden layer	1
Number of neurons in hidden layer	13
Number of output layer	1
Learning rate	0.01
Learning cycle	6
epochs	1000

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RESULTS AND DISCUSSIONS

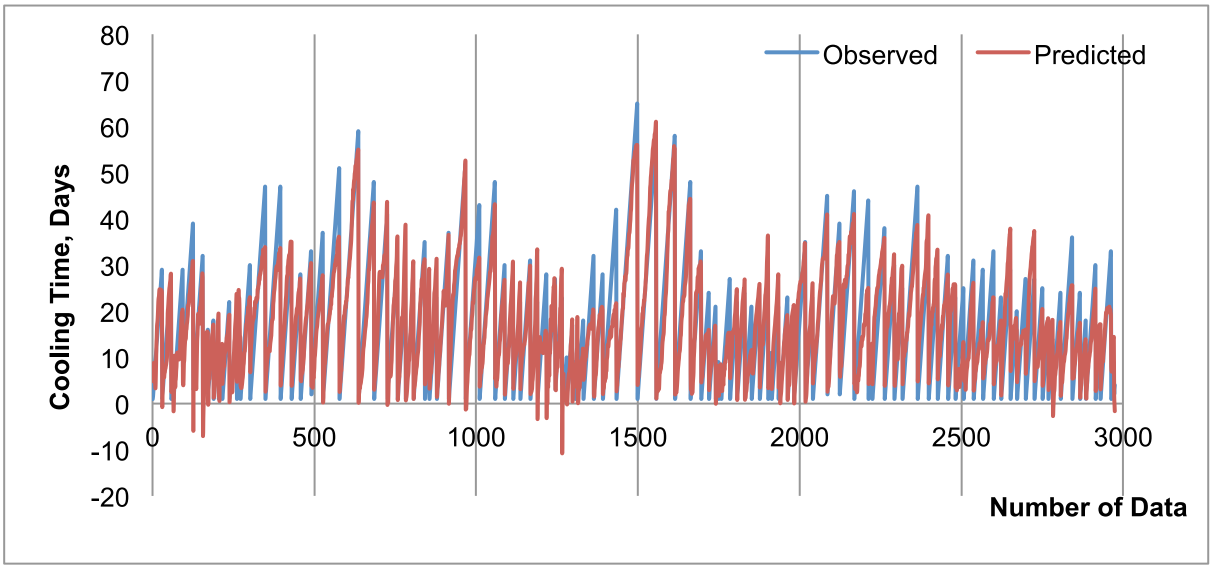
Two emerging soft computing techniques, namely; GP and ANN were utilized in this study to explore the predictive capability for *CT* required to drop T_0 at any interval within initial cooling period at construction phase of the concrete dam.

Tab. 5 shows the best three GP models that were formulated using GP technique. The values of R, MSE and MAE given in *Tab. 5* is for validation data set. Values of R closed to 1 and low MSE and MAE values indicate the data were more fitted. Thus, model 1 was selected as the best compromise between others.

Tab. 5 - Different GP based models

Rank	***MSE***	***MAE***	***R***	***Expressions***	
1	33.928	4.402	0.88223	$CT = \Delta t + \dfrac{-17.1\Delta t Sin(Sin(T_w))}{p_1 P_f T_w} + \dfrac{8.56\Delta t}{0.482 + p_1 P_f + 2.09 T_w p_1{}^2 \Delta t - 0.482 p_1{}^{\Delta t}}$	(8)
2	33.863	4.408	0.88223	$CT = \Delta t + \dfrac{-19.4\Delta t Sin(Sin(Sin(T_w)))}{p_1 P_f T_w} + \dfrac{8.1\Delta t}{0.363 + p_1 + p_1 P_f + 1.46 p_1 \Delta t}$	(9)
3	34.045	4.409	0.88148	$CT = \Delta t + \dfrac{-15.4\Delta t Sin(T_w)}{p_1 P_f T_w} + \dfrac{8.62\Delta t}{0.483 + p_1 P_f + 2.09 T_w p_1{}^2 \Delta t - p_1 P_f (2.09 p_1{}^2)^{\Delta t} - 0.483(2.09 p_1{}^2)^{\Delta t}}$	(10)

Fig. ***2*** *a* shows how well the proposed ANN model fit the experimental data during training process. *Fig.* **2***b* - *Fig.* **2***d* represents performance plot, error histogram plot and regression plot at the learning phase of an ANN.



(a)

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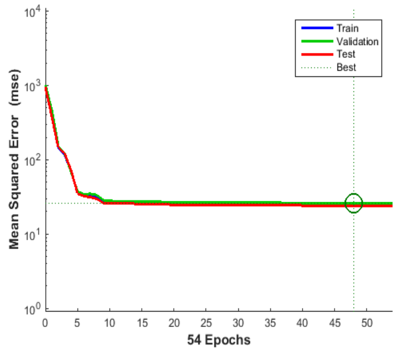
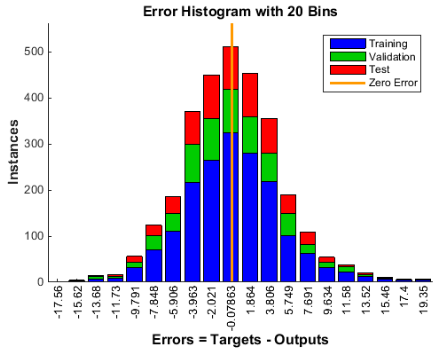
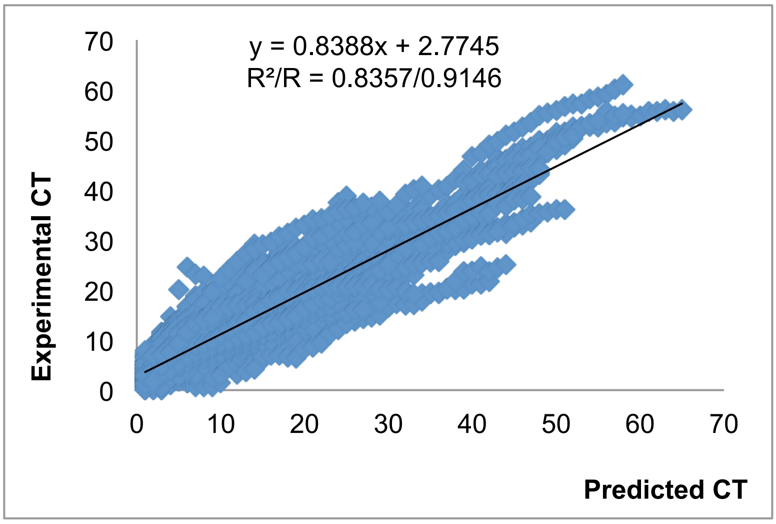


(b)



(c)



(d)

Fig. 2 - Overall statuses during training process in ANN: (a) solution fit plot during ANN training, (b) performance plot, (c) error histogram and (d) regression plot

Due to the lack of previously developed rational model predicting *CT* required to drop T_0 at any interval within an initial cooling period encompassing the influencing variables considered in this study, it is not possible to conduct a comparative study of the results obtained from this study with the previous studies. Based on the rational hypothesis, Smith [29] suggested the following criteria for judging the performance of a model:

- ✓ If a model gives |R|>0.8, a strong correlation exists between the predicted and measured values [30].

It can be seen from *Tab. 5* and *Fig. **2**d,* entire GP and ANN model respectively have R value greater than the suggested good fit (|R|>0.8), which indicates that both models have a good predictive ability. MSE for GP and ANN model is 33.86 and 24.49 respectively. The value of R close to 1 and low MSE value were sought for better accuracy of model.

Comparison of predicted outputs from ANN model was well fitted with real *CT* during training of ANN as shown in *Fig. **2**a.* Performance plot shown in *Fig. **2**b* specifies that LM learning algorithm retrieves the result in just a few epoch. The maximum number of epochs taken by the

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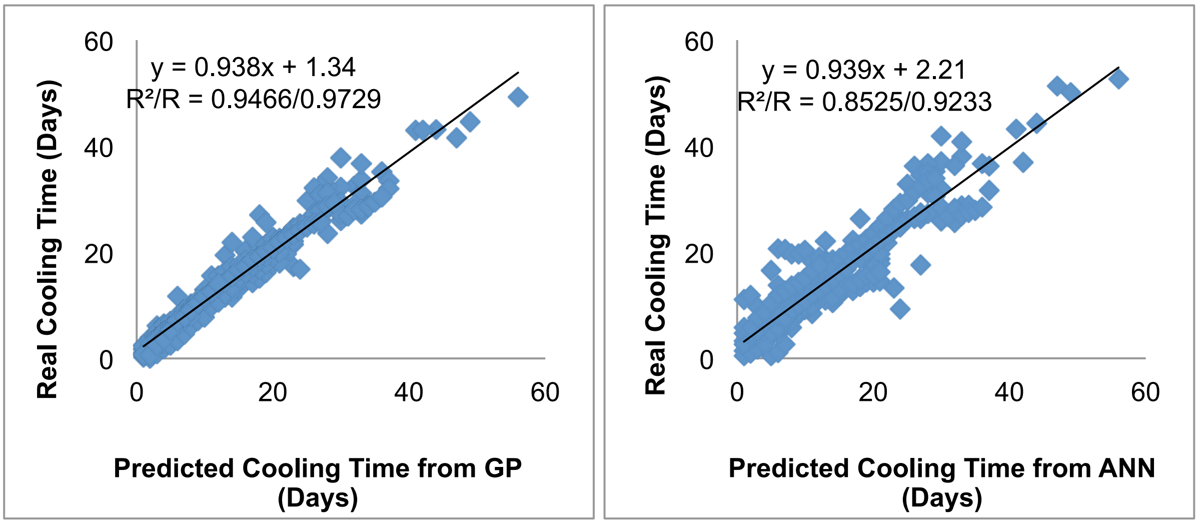
model was 48, which clearly indicates that the time taken from ANN model to predict *CT* was less. Error histogram displayed in *Fig.* ***2****c* represents the error during ANN training, calculated error are within the range of -17.56 to +19.35.

In order to determine the prediction capability of the proposed models, comparisons were made between the predicted values of *CTs* from GP and ANN model with real *CTs* (data from monolith 5#) that were not included during analysis by plotting the graph as shown in *Fig.* ***3***.



(a) (b)

Fig. 3 - Comparison between real CT and predicted CT at testing phase for monolith 5#: (a) with GP model and (b) with ANN model

It is obvious from *Fig.* ***3***, during testing phase the predicted and real *CTs* were strongly correlated with a linear relationship with R^2/R of 0.9466/0.9729 and 0.8525/0.9233 from GP and ANN model respectively. Comparing these data in terms of statistical terms, the value of R from ANN is higher than from GP during training and validation phase, but lower than from GP at testing phase, so it is hard to say which model is more reliable. Each model uses its own algorithm to select the random data for training and validation, so it is concluded that reliability of model solely depends on data. Therefore, a low value of errors and higher values of R^2/R more is certainty, rather than stick on some model.

Moreover, the absolute error and the relative error were calculated to determine the accuracy of the proposed models at testing phase. The absolute error was calculated by subtracting the real *CT* with the predicted *CT* from the proposed models. The relative error was determined by dividing the absolute error with the real *CT* and then expressing it in percentage form. The mean absolute error from GP and ANN model is 0.392 and 1.284 respectively whereas; the mean relative error from GP and ANN model is 6.79% and 21.26% respectively. Comparing these statistical values, both the mean absolute error and mean relative error indicates that the errors were significantly low for GP model. These amounts of errors are acceptable in concrete technology, which clarifies that the proposed model was capable of generalizing the input and output variables with reasonably good predictions.

Fig. ***4*** shows the comparative study of output predicted (*CT*) from GP and ANN model with real *CT* required to drop T_0 to T_e. Also, comparisons have been made with the output from practical formula proposed by Zhu [6]. Further, the derived models have been applied to check the

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CT required to drop T_0 up to T_e for different lifts of monolith 5# having different *CT* at different height (from bottom) as shown in *Fig. **5***.

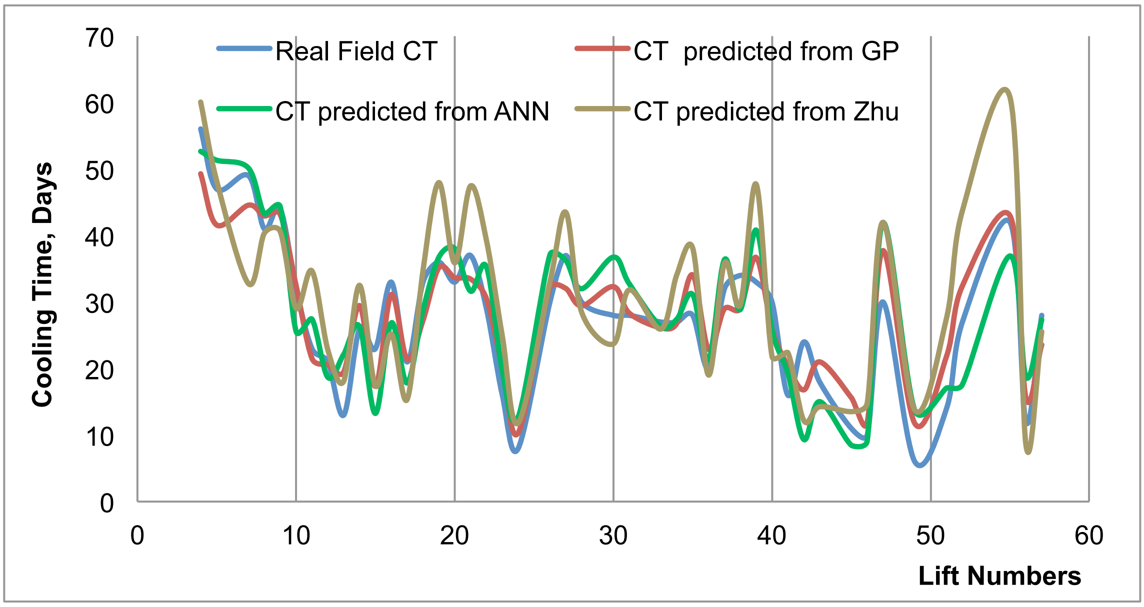
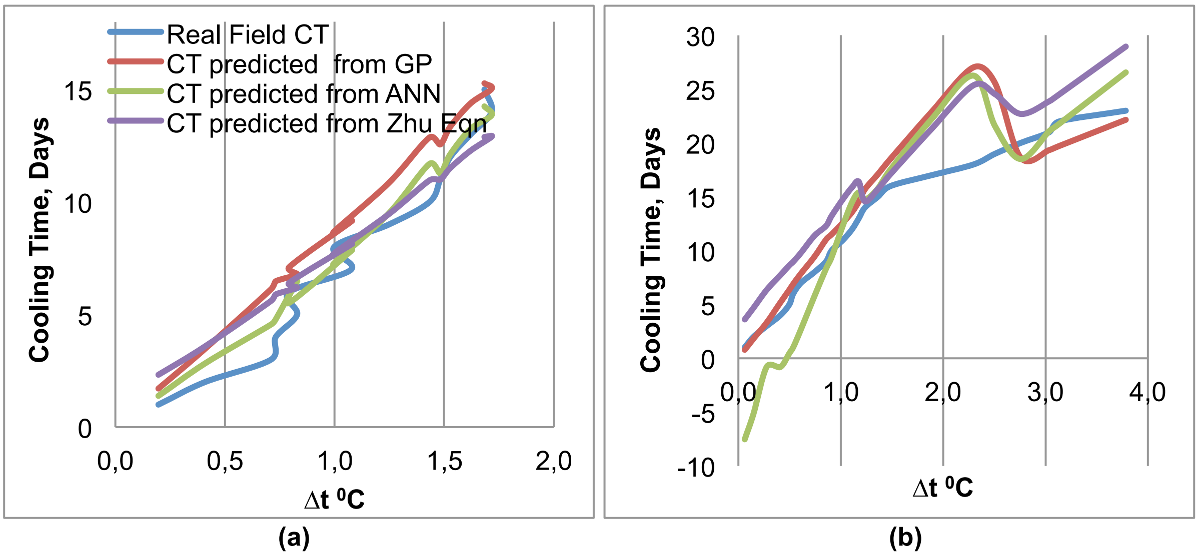
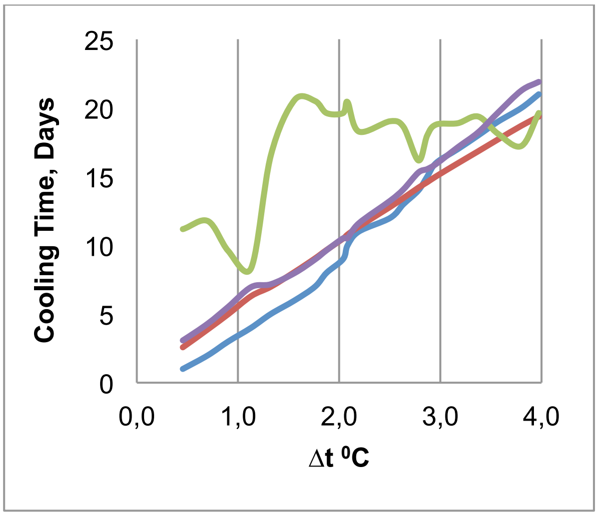
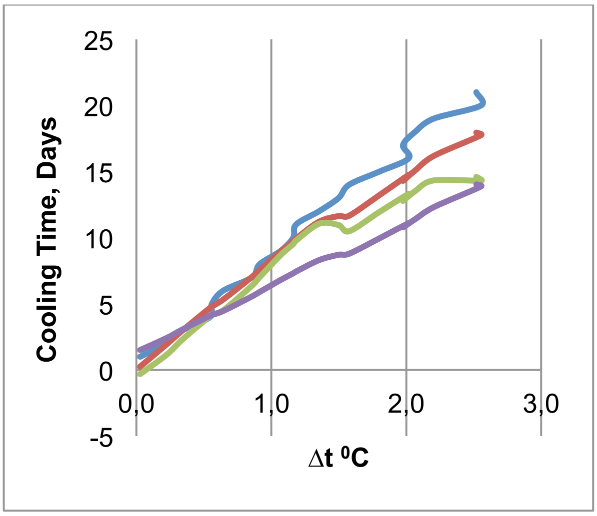


Fig. 4 - Comparison between the results from proposed models (GP and ANN) with real filed data (monolith 5#) and output from practical formula proposed by Zhu




Cooling Time, Days
25
20
15
10
5
0
0,0
1,0
2,0
3,0
4,0
Δt ⁰C

(c)


Cooling Time, Days
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5
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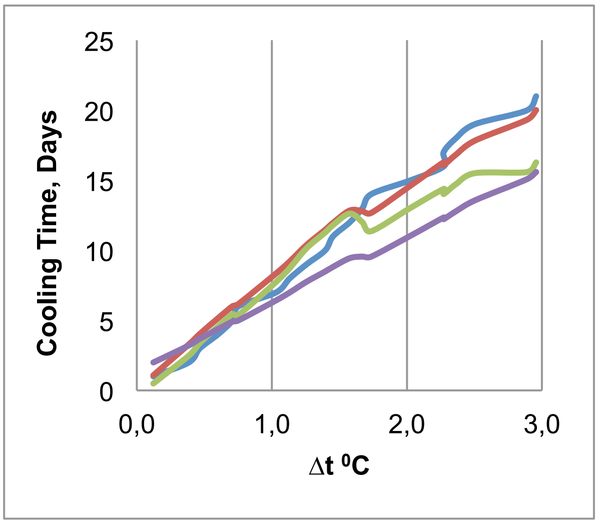
-5
0,0
1,0
2,0
3,0
Δt ⁰C

(d)


Cooling Time, Days
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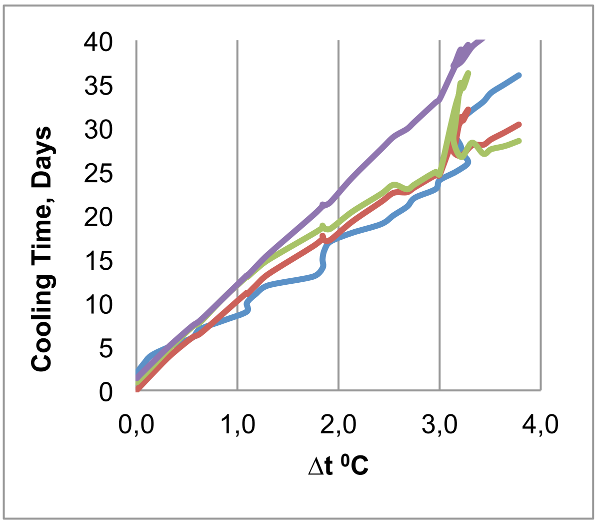
1,0
2,0
3,0
Δt ⁰C

(e)


Cooling Time, Days
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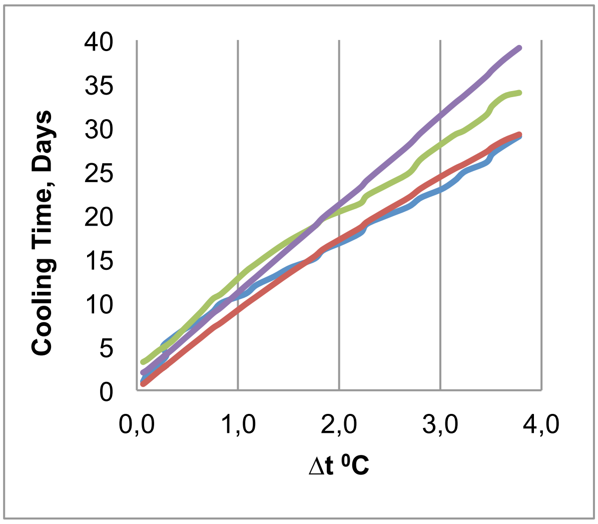
4,0
Δt ⁰C

(f)


Cooling Time, Days
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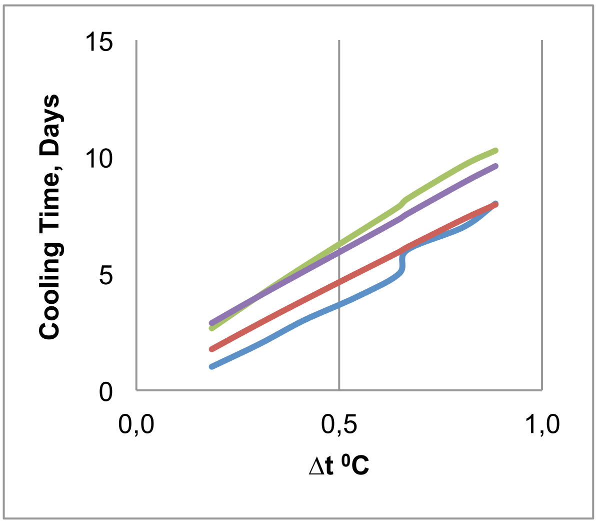
Δt ⁰C

(g)


Cooling Time, Days
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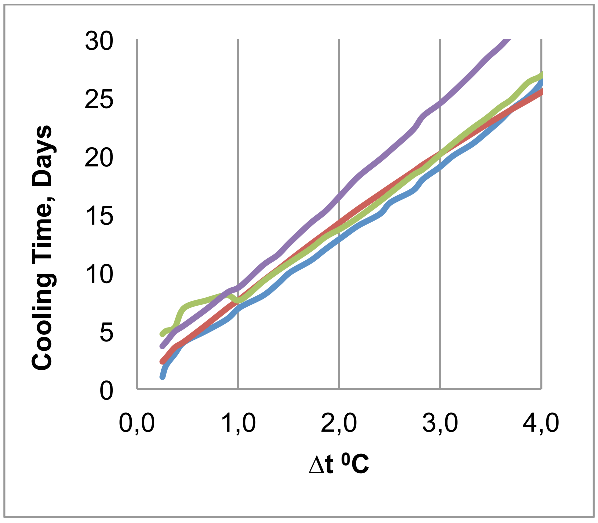
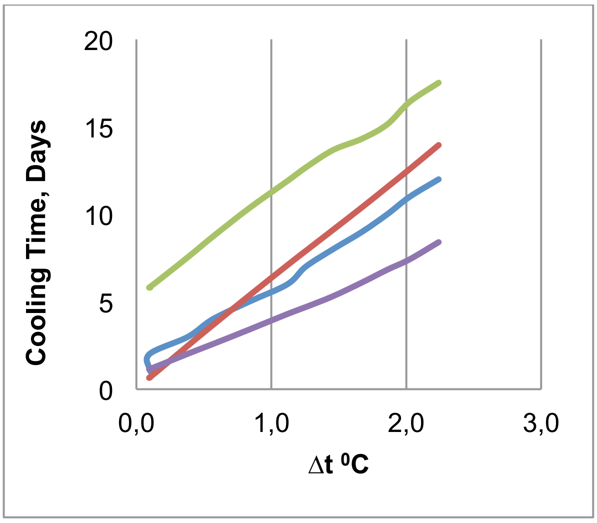
0,0
0,5
1,0
Δt ⁰C

(h)



(i)



(j)

Fig. 5 - CT required for dropping T_0 up to Te for monolith 5#: (a) Lift 5 at height 12 m, (b) Lift 9 at height 24 m, (c) Lift 12 at height 34 m, (d) Lift 16 at height 45 m, (e) Lift 17 at height 48 m, (f) Lift 19 at height 54 m, (g) Lift 22 at height 63 m, (h) Lift 24 at height 69m, (i) lift 34 at height 99m and (j) lift 56 at 163.5m

Note: *Blue line, Red line, Grey line and Purple line indicates the same for Fig.* ***5****b - Fig.* ***5****j as used in Fig.* ***5****a.*

As shown in *Fig.* ***4*** *- Fig.* ***5****j, c*omparing the prediction outputs from proposed GP and ANN models with the results obtained from the practical equation proposed by Zhu, more accurate and consistent predictions have been obtained using the proposed models. This clearly indicates that, parameter *"P_f"* has the influence to the target parameter and should be considered while predicting *CT*. The comparison of the calculated results from proposed models and real *CTs* shows that GP model is able to predict *CT* with acceptable accuracy.

Sensitivity analysis was performed to evaluate the relative impact of input variables on target variable within the GP model. The sensitivity of the model with respect to each input parameters is defined as follows:

$$Sensitivity = \left| \overline{\frac{\partial_{stability}}{\partial_{x_i}}} \right| * \left| \frac{\sigma_{x_i}}{\sigma_{stability}} \right| \qquad (11)$$

Where: δ = partial derivate operator, σ = standard deviation, and x_i is the i^{th} input parameter [19].

A summary of sensitivity, percent positive and percent negative values for the GP model is shown in *Tab. 6*.

Tab. 6 - Sensitivity study of the GP model

Input*	***Sensitivity***	***Percent positive***	***Percent Negative***
p_1	0.2462	0	100
Δt	0.9936	100	0
T_w	0.2098	90	10
P_f	0.1704	0	100

* As defined in expressions in *Tab.* ***2***.

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 [19].

Sensitivity analysis results shown in *Tab. 6* clarify that input variable p_1 has a negative impact on the target variable, whereas remaining input variables Δt and T_w possess high positive impact on the target variable. Further, construction parameter "P_f" shows 100 percent negative impact with sensitivity 0.17 to the target variable, which confirms that the assumed hypothesis is true.

It must be kept in mind that, the proposed models for predicting *CT* are valid within the minimum and maximum range of parameters given in *Tab.* ***2***. These models were derived from three monoliths of the research project, as more data from different project become available, the proposed models can be improved to make a more precise prediction for the wider range. Recently, a numbers of large concrete dams are under construction around the world. This research will be helpful in developing countries where opportunities of high concrete dams are anticipated to build in coming days.

CONCLUSION

The GP and ANN models developed in this study are used to predict *CT* required dropping T_0 at any interval within the initial cooling period during the construction phase of concrete dam. In this regard, data available from recently constructed high concrete double curvature arch dam (Xiluodu) in China, were used to derive the proposed models. 108 numbers of lifts from monoliths 15#, 16# and 23# containing 2974 rows of each input and output variables were used during analysis. The GP model was trained and validated with 50% - 50% of data whereas, the ANN model was trained, validated and tested with 60% - 20% - 20% data respectively (chosen randomly in both cases). Beside validation, 45 numbers of lifts from monolith 5# containing 257 rows of each input and output variables were used for testing (checking the applicability) of the proposed models. The following conclusions were drawn from this research:

(1) The proposed GP model is capable to sort out the complication on adjusting the water cooling parameters (T_w and q_w) to control T_0 in recent construction of concrete dams. Using this developed model, *CT* required to drop T_0 can be calculated easily and accurately varying the parameters involved in temperature control process prior to construction, which helps to take an efficient and effective decision of temperature control plan in advance.

(2) As has been observed, both the models have R value (0.8822 and 0.9146 from GP and ANN model respectively) greater than suggested good fit (|R|>0.8) during training and validation. Beside validation, testing the models capabilities with an independent data set, R value is 0.9729 and 0.9233 from GP and ANN respectively, which indicate that the performance of the proposed models are admirable.

(3) The derived GP and ANN models predicted *CT* required dropping T_0 with an agreeable error. The mean absolute error (0.392 and 1.284) as well as the mean relative error (6.79% and 21.26%) for GP and ANN model respectively, which is acceptable in concrete technology, as observed during the testing process of the model. Further, comparing the prediction outputs from proposed models with the real *CTs* and output predicted from the practical formula proposed by Zhu, results obtained from the proposed GP model are convincing.

(4) Sensitivity analysis results clarify that; construction parameter "P_f" has 100 percent negative impact on target variable, which proves that the assumed hypothesis is true. Thus, it is concluded that the parameter "P_f" should be considered while predicting *CT* to drop T_0.

(5) Both models have their own advantages and can be used accordingly. Obtained

formulas from the GP model for predicting *CT* is simple whereas, the time for developing GP model is more than ANN model. Further, despite of the acceptable performance of ANN model (capability of predicting *CT* in less time), it is not able to explain the underlying principle of prediction and unable to generate prediction formulas.

(6) The overall findings of the present study indicate that the proposed models for predicting *CT* to drop T_0 are reliable and applicable to concerned parties and it could save their time and cost of conducting sophisticated experiment that requires specialized equipment and expertise.

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