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Research Paper

PREDICTING TEMPERATURE OF MASS CONCRETE AT CONSTRUCTION PHASE OF CONCRETE DAMS USING GENETIC PROGRAMMING AND ARTIFICIAL NEURAL NETWORK

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Effective decision on temperature control plan can be taken in advance by designer and contractor, understanding the influence of the parameters that affects the temperature development of concrete at construction phase of massive concrete structures. This study is intended to formulate the relation between temperature development in mass concrete at early ages with thermal properties of concrete, water cooling parameters, age of concrete and environment temperature utilizing Genetic Programming (GP) software “Eureqa” and Artificial Neural Network (ANN). Data available from recently constructed high concrete arch dam were used to achieve the purpose Value of correlation coefficient (R) is 0.9616 and 0.9696 respectively from GP and ANN model whereas Mean Squared Error (MSE) value is 0.8293 and 0.6497 for GP and ANN model respectively. Relative impact on the model due to inputs parameters is evaluated through sensitivity analysis. Further, verification of the models with an independent data sets hold a good agreement with the real field data. These proposed models will be beneficial in-terms of cost saving and time for sophisticated laboratory works for temperature measurement of mass concrete at construction phase.

Keywords: Mass concrete, Early age, Genetic programming, ANN, Prediction

INTRODUCTION

Cement hydration is an exothermic process which plays a vital role in the temperature development of early-age concrete.From decades of practical experience and theoretical considerations, it well known that the qualities of concrete and concrete structures are affected by early age temperatures and temperature induced stresses. Normally, temperature rises of concrete vary depending upon many parameters including cement composition, fineness, aggregate contents,thermal properties of concrete (density

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of concrete, specific heat of concrete, diffusivity and coefficient of thermal expansion) and section geometry.

However, in massive concrete structures (like concrete arch dams), which are constructed from individual cantilever blocks with 1-5 m- 3.0 m lifts, temperature development at early age depends upon heat of hydration of cement and other parameters like; lift height of the block, placing time interval between successive lifts, time of placement (hot season or cold season) and environmental temperature (E_t) of the project site. Further, minimizing the temperature rises in massive concrete structures is realized by flowing chilled water through the interconnected pipe network embedded in concrete during construction. Thus, it can be said that, temperature development in massive structure depends upon water cooling parameters like;spacing of the cooling pipe, inlet temperature of the cooling water (T_w) and rate of flow of cooling water (q_w).

Measurement of concrete temperature at construction phase of massive concrete structure requires high costs and sophisticated instruments. ACI 207.1R (ACI) discusses several approximation methods that are appropriate for simple evaluation. The Carlson (Carlson, 1937) and Schmidt (Rawhouser and Clarence, 1945) methods are step by step integration techniques used for computing temperature gradients with 1-D heat flow with reasonable simple boundary conditions and are adopted to spread sheet solutions on personal computers. Due to iterative procedure, this method is time-consuming when performed manually. The Portland Cement Association (PCA) is another commonly used method for temperature prediction in concrete members. This method calculates 10 ^{0}F temperature rises in 100 lb cement. Further, this method lacks of providing the information on time of maximum temperature, does not quantify the temperature difference and assumes the dimension of concrete member of at least 1.8 m (6 ft).

The current practice to predict temperature distributions over time in concrete dam is to use finite element analysis toolsand a number of researches have been done for determining the temperature distribution of concrete dams at construction phase with the aid of these tools (Ding and Chen, 2013; Liu *et al.*, 2013; Ha *et al.*, 2014; Li *et al.*, 2014; and Liu *et al.*, 2015). Computation of temperature distribution in mass concrete using FEM requires a good knowledge of FEM software and modeling techniques.(Najafi and Ahangari, 2013),conducted an research on predicting concrete temperature during curing using regression and artificial neural networks utilizing time (h), water cement ratio (W/C), environment temperature, aggregate content, diameter and specimen height as an input variable.However, this method does not consider water cooling parameters which are main important factors that affect temperature rises in massive concrete structures.

Over the last two decades, soft computing technique like ANNs, fuzzy neural network systems and GP have been gaining popularity for solving complex problems in the field of civil engineering. ANN method is widely used by many researchers for determining different properties of concrete (Kim and Kim, 2002; Singh and Kotiyal, 2013; and Chopra *et al.*, 2015) and concrete structures (M *et al.*, 2001; Arslan, 2010; and Golafshani *et al.*, 2015). Among these soft computing techniques, GP is another branch of machine learning methods which automatically generates computer models based on the rule of natural genetic evolution. Due to 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 (Kishore *et al.*, 2000; Adhikary *et al.*, 2015; and Mazari and Ziazi, 2015) different types of GP likes: gene expression programming (Cevik and Cabalar, 2009; and Gandomi *et al.*, 2011) and multi gene-genetic programming (Golafshani *et al.*, 2015) 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 (Eureqa). There have been some scientific efforts aiming to apply Eureqa for solving some problems in civil engineering field (Ricketts and Carter, 2011; and Mazari and Ziazi, 2015).

Thus, in this research, an effort have been made to develop the robust prediction model for predicting temperature rises in mass concrete at early age during construction phase of concrete dam with the help of two emerging data mining techniques namely; Genetic programming Software "Eureqa" and Artificial Neural Network (ANN). Co-efficient of pipe cooling (p_1) which is related to thermal properties of concrete (density, thermal conductivity, specific heat capacity of and diffusivity) and water cooling parameter (qw, diameter of cooling pipe, length of cooling pipe, spacing of cooling pipes),T_w,E_t and age of cement (A_c) are provided as an input parameters and temperature of mass concrete (T_c) is taken as output parameter in this study.

DATA SOURCE AND ANALYSIS METHOD

In order to determine the temperature on concrete block (T_c) at an early cooling period during construction of high concrete dam, data were taken from the project named "Xiluodu high concrete arch dam" which was recently constructed and located in the lower reach of the Jingsha River, Yunnan Province, in southwest China (Li *et al.*, 2014). During the construction of the project, optical fiber and thermometer was embedded to monitor the temperature of concrete at each and every lifts. The data from monolith 15 and monolith 16 recorded from optical fiber and thermometers in different time interval within a day for each and every lift were chosen in this study.

Thermal properties of concrete 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 were as the real situation of the project. Different type of pipe spacing (H:V) as 1.5 m*1.5 m, 1.0 m*1.5 m and 1.0 m*1.0 m, lit height of 1.5 m as well as blocks constructed at different season were considered in this study. A thermal property of concrete (Concrete Type A)used to obtain the objective of this research is listed in Table 1.

Temperature development of mass concrete in construction period depends upon placing temperature of concrete and the time of construction (hot season or cold season). In the project, the placing temperature of concrete at hot season and cold season was capped around 9 °C and 11 °C respectively and placing temperature was capped not more than 12 °C all around the year (Lu *et al.*, 2012). The type of cement used for preparing the concrete is Huaxin Cement (Zhaotang) Co. Ltd. manufactured by Guang'an Sichuan TengHui Cement factory. To reduce the temperature rise of concrete, certain

Table 1: Thermal Properties of Concrete				
	Density (ρ) Kg/m^3	Thermal Conductivity (λ) Kj/(m h ^{0}C)	Specific Heat Capacity (C) Kj/(kg	Diffusivity (a) m^2/day
Concrete Type A	2592.58	7.35	1.08	0.063

amount of coal ash were used while preparing the concrete. Table 2 shows, types of constituents mixed to prepare 1 m^3 of concrete for the above mentioned types of concretes.

Concrete temperature data and water cooling data from placing date to initial cooling period were identified those has been measured almost at the same time for individual lifts. Time period from the placing time of concrete to the nearby point of concrete temperature measurement is A_c in hour and finally hour is transfer to day. Data from monolith 15 having 715 numbers of rows of each variable were for building the GP and ANN model. While, the data from monolith 16 having 408 numbers of rows of each variable were used for final testing of the proposed models. Further coefficient of pipe cooling p_1 (which is dependent on q_w) can be derived from the following relationship (Zhu, 2014).

$$p_1 = k_1 (ga / D^2)^s \quad ...(1)$$

where,

$$k_1 = 2.08 - 1.17\xi + 0.256\xi^2 \quad ...(2)$$

$$s = 0.971 + 0.1485\xi - 0.0445\xi^2 \quad ...(3)$$

$$\xi = \frac{\lambda L}{c_w \rho_w q_w} \quad ...(4)$$

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

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

where,

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

where, a is thermal diffusivity of concrete (m^2/day), A_c is age of concrete (days), b is outer radius of concrete cylinder (m), c is inner radius of concrete cylinder (m), c_w is specific heat of cooling water (kJ/Kg^{0}C), D *is* diameter of concrete cylinder (m), L is length of pipe (m), q_w is flow of cooling water (m^3/h), r_0 is inner radius of non-metal cooling pipe (m), S_1 is horizontal spacing between cooling pipes (m), S_2 is vertical spacing between cooling pipes, T_w is inlet temperature of cooling water (^{0}C), λ is coefficient of thermal conductivity of concrete (kJ/mh ^{o}C), λ_1 is coefficient of thermal conductivity of non-metal cooling pipe (kJ/mh ^{o}C), ρ_w is density of cooling water (kg/m^3) and $\eta = \lambda/\lambda_1$.

In order to develop the GP and ANN prediction models, the statistics of the input variables and target variable are shown in Table 3.

METHODOLOGY

Genetic Programming, Eureqa and Automatic Solution Seeking

Genetic Programming (GP), which was first

Table 2: Constituents for Concrete										
Type of Concrete Unit	Water Consumption Kg/m^3	Cement	Coal Ash Kg/m^3	Sand Kg/m^3	Small Stone Kg/m^3	Medium Stone Kg/m^3	Big Stone Kg/m^3	Extra Large Stone Kg/m^3	Water Reducer Kg/m^3	Air Entraining Agent Kg/m^3
Concrete Type A	90	143	77	511	354	354	531	531	1.537	0.044

Table 3: Statistics of the Input and Target Parameter

Rank	Input			Target T_c (°C)	
	p_1	T_w (°C)	E_t (°C)	A_c (Days)	T_c (°C)
Mean	0.041	9.11	24.99	10.91	22.35
Median	0.041	8.8	24.8	5.26	23.05
STDEV*	0.0065	1.58	3.55	12.69	3.29
Variance	4.25E-05	2.51	12.62	161.09	10.87
Minimun	0.047	16	33.7	57.75	26.58
Maximum	0.023	6	18.3	0.15	8.75

Note: * = Standard deviation.

introduced by John Koza (1992) is another branch of machine learning methods, which automatically generates computer programs based on the rule Darwinian natural selection and biologically inspired operations to solve the user-defined task. (Mazari and Ziazi, 2015) stated, unlike soft computing techniques, GP is not considered as black box model and outputs are in form of semi-complex mathematical equations, which could be relevant to apply for real problems. 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 (Mazari and Ziazi, 2015).

The Eureqa software, sometimes called the robot scientistis a fairly new, publically available product from Cornell Creative Machines Lab http://creativemachines.cornell.edu/eureqadeveloped by Prof Hod (Schmidt and Lipson, 2009), which is aimed at optimization and automated symbolic regression tool for detecting equations and hidden mathematical relationships in raw and is based on GP. 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 (Ricketts and Carter, 2011).

Development of the Empirical Model Using GP

In this study, basic arithmetic operators (+, -, *, /) trigonometric operator (sin, cos) and some basic exponential functions (exponential, natural logarithm, square root, factorial and power) are utilized to get the optimum GP model. Following function is used to obtain the meaning-full hidden relationship between T_c and the influencing variables:

$$T_c = f(p_1, T_w, A_c, E_t) \quad ...(7)$$

In order to identify the function T_c, the set of data's from monoliths 15 (715 numbers of each variable) were divided into two parts: 70% for training process and 30% for validation to build the GP model: Divisions of dataset were shuffled randomly from a random set of data. According to (Marref *et al.*, 2013) division of data used for building the model and validating the model can be changed while satisfying two opposing criteria: (i) to account for a diversity of data points while deriving the model,the size of the dataset used in training should be as large as possible and (ii) for evaluation, the size of the dataset used should be as large as possible to avoid over fitting in the derived model.

Artificial Neural Network

ANN or simply Neural Network (NN) is a non-linear modeling tool that can solve many engineering problems without any mathematical equations (Saûuddin *et al.*, 2016).The architecture of an

ANN consists of artificial neurons, which are analogous to natural neurons in the brain. Typical neural network architecture consists of one input layer, one or more hidden layer, and one output layer (Knight and Kevin, 1990). Like natural neurons, ANN undergoes some learning procedure before they can actually work. In general, different kind of learning algorithms is used by ANN whose basic procedure is to adjust weights between nodes for mapping input with output.

Development of 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 layer, numbers of neurons in each hidden layer and transfer functions for hidden layers and output layers (Chopra *et al.*, 2015). In this study, three-layered feed-forward network was trained with Back-Propagation (BP) training algorithm and Levenberg-Marquardt (LM) was utilized as a learning algorithm. LM is more advanced learning method based on BP, which provides the numerical solution to the problem of minimizing a non-linear function quickly. BP algorithm for all multi-layered networks uses a gradient descent technique to minimize the error for a particular training pattern in which it adjusts a weight by a small amount of time (Cachim, 2011). The network error is passed back to the input layer from the output layer in each run until no further improvement in the MSE value is found (Alshihri *et al.*, 2009). Number of hidden layers and number of neurons in each layer are responsible for producing accurate results to create a Multi-layered feed forward networks (MLP). Although there is no any rule that describes the same but the numbers of hidden layers and neurons in each layer must be chosen based on experience, and a few numbers of trials are usually necessary to determine the best configuration of the network (Cachim, 2011).

A program code is written in MATLAB SOFTWARE (R.2014.b) to perform the necessary computations. The same dataset used for developing GP model were taken to construct an ANN. The input data set were randomly divided into three parts: 70% for learning process, 15% for validation phase and 15% for test phase. The ANN developed in this research consists of four neuron (inputs) in input layer and one neuron (output) in output layer. The numbers of neurons in the hidden layer was adjusted 10 after doing many trial and errors. A non-linear hyperbolic tangent sigmoid function and linear function were used as a transfer functions in hidden and output layer respectively due to their ability to learn complex non-linear relation between input parameter and output parameter (Chopra *et al.*, 2015). Network training parameters as learning rate, epochs, and number of learning cyclesadopted to construct an ANN model are 0.01, 1000 and 6 respectively.

RESULTS AND DISCUSSION

In this study, two emerging data mining techniques were utilized to predict the temperature in mass concrete blocks at construction phase of concrete dam. Different types of GP-based models were evaluated as shown in Table 4. The performances of the models were evaluated based on their predictive powers in terms of correlation coefficient (R) and MSE. The value of R and MSE given in Table 4 are for the validation set of data. The R closer to

Table 4: Different GP-Based Models

Rank	MSE	R	Expression
1	0.8293	0.96156	$T_c = 22.4 + \frac{-808}{E_t Exp(A_c)} \frac{16.2 + 3.29Cos(-221E_t)}{Exp(A_c)} + \frac{23.9 + 74.2P_1A_c - 3.75A_c}{Tw}$
2	0.8504	0.96067	$T_c = 21.6 + \frac{-788}{E_t Exp(A_c)} \frac{15.5 + 3.29Cos(-221E_t)}{Exp(A_c)} + \frac{29.8 + 74.3P_1A_c - 3.75A_c}{Tw}$

1 and low value of MSE indicates the data were more fitted. Thus, model no. 1 is considered as the best compromise between other.

Figure 1b demonstrates the regression plot of the developed ANN model. According to Smith (1986), if a model gives |R|>0.8, a strong correlation exists between the predicted and measured values.

As shown from the Table 4 and Figure 1b theentire derived GP model and ANN model have |R|>0.8, thus it can be said that, the proposed models havepromising predictive ability.

Figure 1a shows how well the proposed GP-based solution fit the experimental data for model 1. X-axis denotes the number of data used to derive the GP model.Performance plot shown in Figure 1c denotes that LM learning algorithm the algorithm retrieves the result in just a few epoch. The maximum number of epochs taken by the model was 24, which clearly indicates that the time taken for the prediction from ANN was less.

To determine the prediction ability of the proposed GP and ANN model, comparison have been made between predicted and observed T_c (with the data that were not used for developing the models) as shown in Figure 2. Predicted T_c at testing phase was much closer to the observed T_c with coefficient of determination (R^2)/correlation coefficient (R) 0.8085/0.8991 and 0.7657/0.8750

Figure 1: Performance of GP-Model: (a) Solution Fit Plot of GP Model, (b) Regression Plot of an ANN Model, and (c) Performance Plot of an ANN Model

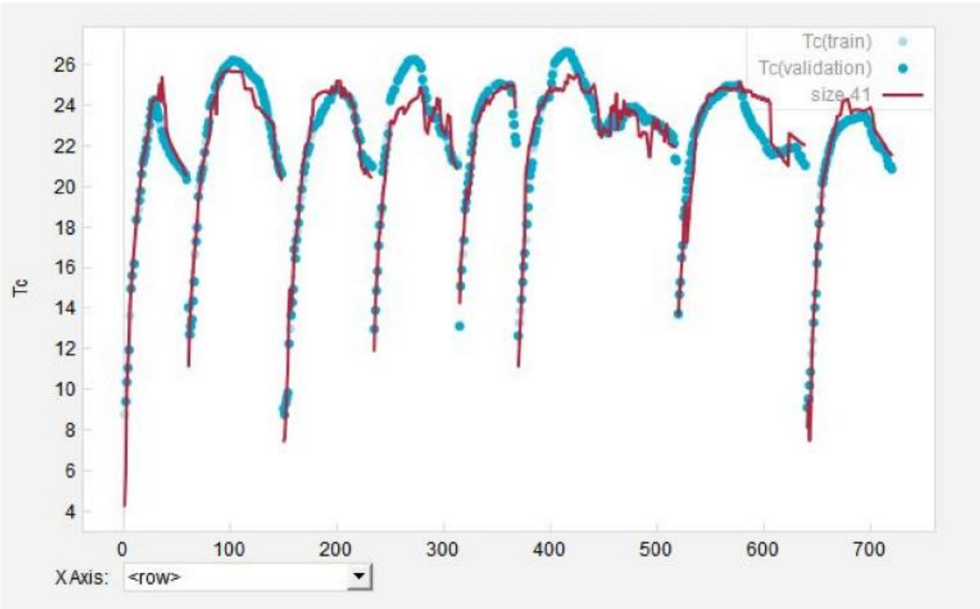
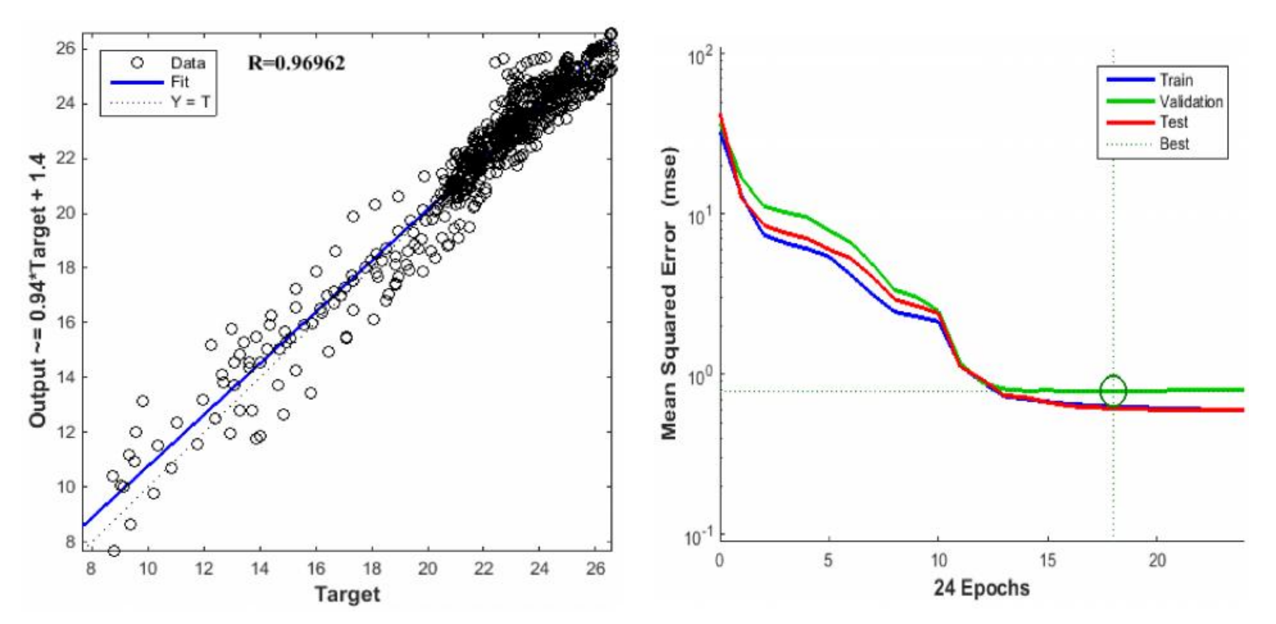


Figure 1 (Cont.)



from GP and ANN model respectively which is greater than the suggested good fit. Comparative study of result obtained from GP and ANN model at the testing phase with the real field data has been shown in Figure 3, which indicates that the data were more fitted from GP model. The result showed that the proposed models are capable of generalizing the input and output variables with reasonably good predictions.

The comparison of the calculated results from proposed models and real T_c shows that GP model is able to predict T_c with acceptable accuracy as showed in Figures 3a-3d. Prediction models in this research were developed from the data available from single dam. As more data could be made available, proposed models can be improved to make more precise prediction for the wider range. Therefore, the derived model can

Figure 2: Comparison Between Real T_c and Predicted T_c at Testing Phase: (a) with GP Model and (b) with ANN Model

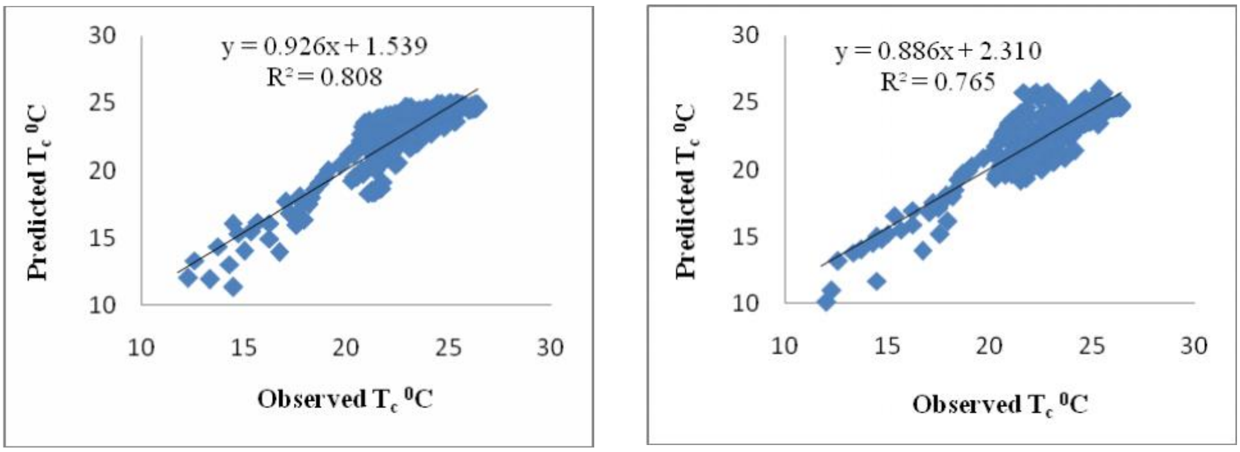
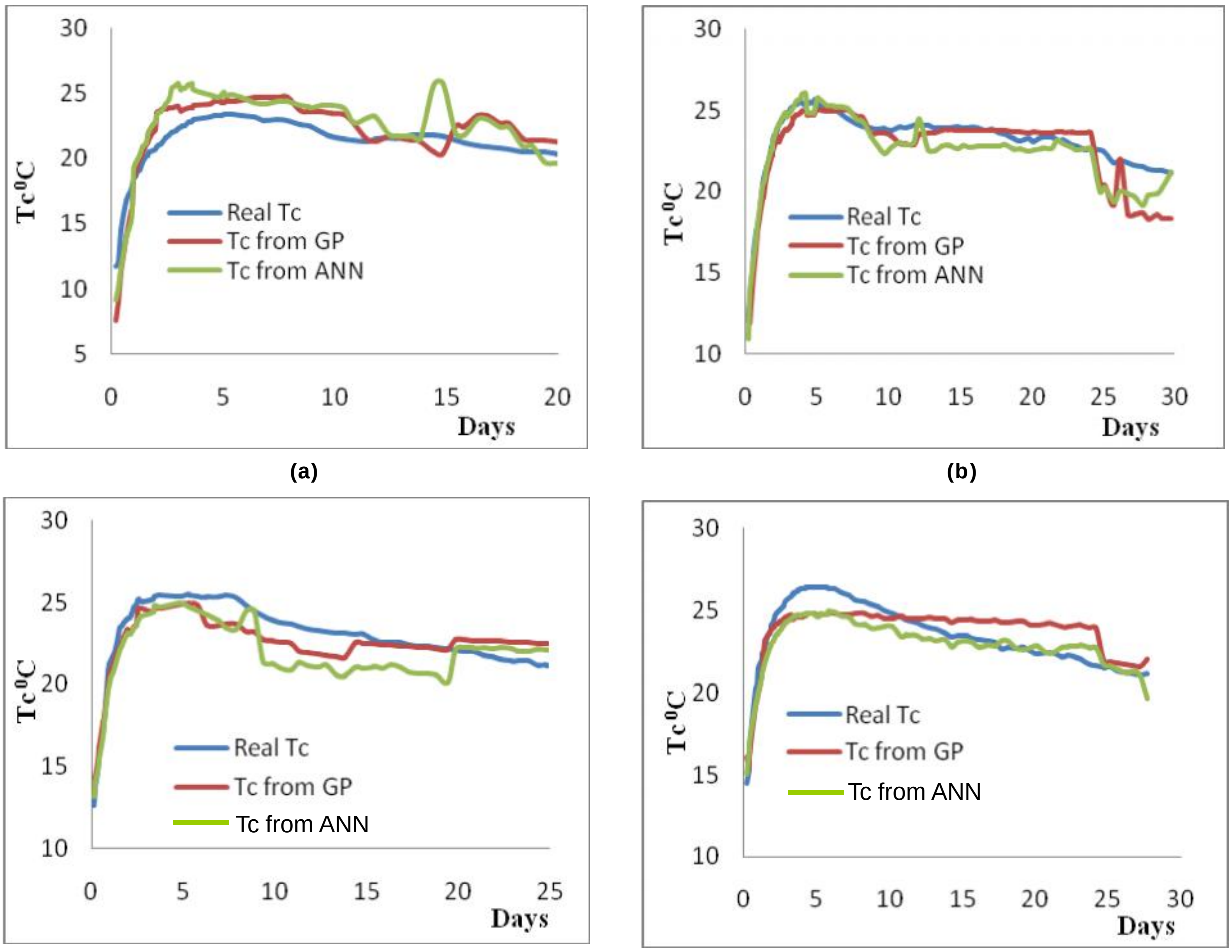


Figure 3: Comparative Study for Real T_c and T_c Predicted from GP and ANN Model: (a) Constructed at 2009/5/18, (b) Constructed at 2009/5/25, (c) Constructed at 2009/8/13, and (d) Constructed at 2009/8/23



(a) (b) (c) (d)

be used in preliminary design stages and should be used carefully for final decision making. Further, each model has its own advantage, time required to predict T_c from ANN model is less while predicting T_c from GP model is simple.

Sensitivity analysis was performed to determine the relative impact of input variable to the target variable within GP model. The term sensitivity is defined as the relative impact within the model that an input variable has on the target variable. For a given model in the form z = f(x, y, …), sensitivity is expressed as follows:

$$Sensitivity = \left|\overline{\frac{\partial_z}{\partial_x}}\right| * \frac{\sigma(x)}{\sigma(z)} \qquad ...(8)$$

where: d = partial derivate operator, σ(x) = standard deviation of x in the input data, σ(z) = standard deviation of z (Eureqa).

The percent of data in which the partial derivative of the target value with respect to the ith input is greater than zero is known as percent positive. This number shows the probability that the increment of the specified input parameter would increase the target value in the model and

Table 5: Sensitivity of the GP-Model

Input Variable*	Sensitivity	Percent Positive	Percent Negative
A_c	6.9691	50	50
p_1	0.26653	100	0
E_t	3.894	53	47
T_w	0.08964	0	100

Note: * As defined in Table 3.

the same concept will be applied for negative value of the aforementioned derivative term known as percent negative (Mazari and Ziazi, 2015). Table 5 includes a summary of sensitivity, percent positive and percent negative values for the GP-based model proposed in this study.

CONCLUSION

Predicting the temperature development in mass concrete is a complex due to the varying thermal properties of concrete with passage of time and many other parameters involved in the process. Recognizing the influence of parameters will be helpful to designer and contractor to take an efficient and effective decision about temperature plan in advance. Based on the result obtained, following conclusion has been drawn from this study:

1. Value of R from both models is close to 1 (0.9616 and 0.9696 from GP and ANN respectively) and MSE value from both model is low (0.8293 and 0.6497 from GP and ANN respectively) which reveals that the performance of model is fairly reasonable.
2. Verification of the proposed models with independent data sets holds good agreement with the real field data which indicates, proposed models are capable of generalizing the input and output variables with reasonably good predictions.
3. Sensitivity analysis reveals that input parameter p_1 and T_w possess positive impact and negative impact respectively to the target variable, whereas the relative impact of input parameter A_c and E_t to the target viable cannot be decided based on sensitivity analysis.
4. Using these proposed models, T_c at construction of high concrete dam can be easily estimated using the variables taken in this study, which will be beneficial in-terms of time saving for sophisticated laboratory experiment.

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