Genetic Programming for Prediction of Heat Stress Hazard in Underground Coal Mine Environment

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Abstract

Working against nature and uncertain environment makes underground mining a hazardous profession. Every year hundreds of miners lose their valuable lives due to mine hazards. Increasing demand for coal necessitates the extraction of coal at a higher rate. As a result, easily minable shallow coal deposits are depleting speedily, and in near future, deep seated deposits will be left for mining by underground methods. With rising depth and deployment of high-capacity machines, increasing heat stress becomes a major hazard in underground mine environment posing threat to the miners' health, productivity and safety. Ignoring the effect of heat stress may lead to dangerous circumstances, even result in death. To avoid such unwanted event, it has become imperative to predict the heat stress to reduce its adverse impact in underground coal mines. Therefore, in this study a detailed field survey is conducted to collect the environmental data of three underground coal mines. Genetic programming (GP) is done to develop relation between the environmental parameters and heat stress, by taking the mine survey data as input. The good correlation coefficient (R=0.9816) is obtained between the GP predicted heat stress and actually measured heat stress, which indicates that GP can be effectively used to predict the heat stress in underground mines. A sensitivity analysis (SA) is done to determine the effect of input parameters on heat stress. The SA results reveled that all six input parameters have considerable effect on the heat stress, however, dry-bulb temperature has the highest effect (0.98) on heat stress.

1. Introduction

Owing to the presence of many unforeseen hazards, underground coal mining happens to be one of the most accident-prone occupations (Cho and Lee 1978). There is every possibility of occurrence of life-threatening events in underground mines, like roof strata collapse, outburst of toxic and inflammable gases, firedamp and coal dust explosions, sudden inrush of water, etc. (Ma et al. 2016; Wang et al. 2018; Dursun 2020). Presence of high heat, humidity and dust in underground mines makes the mine environment more complex and uncomfortable for the miners (Roy et al. 2021). Despite presence of numerous hazards, underground coal mining could not be scaled down due to high energy demand across the globe. Coal meets 60% and 54% of the total energy demand of two leading coal producing countries of the world, China and India, respectively (Gui et al. 2020; Ministry of power Government of India 2020). Due to rising demand of coal, the mine operators are compelled to mine shallow coal deposits with high-capacity machines, which results speedy depletion of easily minable deposits and necessitates mining of deep-seated coal deposits. As underground coal mines are nowadays becoming deep, extended over large area and mined with high-capacity machines, the heat addition from various sources like geothermal gradient, auto-compression of air and heat ejection from machinery becomes high. Therefore, there is prevalence of heat stress in underground coal mine environment.

Heat stress has detrimental effects on the health safety and productivity of underground coal miners. The core body temperature of humans is maintained close to 37°C, which may rise during working in heat stress environment (Lemke and Kjellstrom 2012). In such condition, the central nervous system of workers may get destabilized which may be reflected by the symptom of mental retardation, lack of concentration, and decreased ability to work (Nie et al. 2018). When the core body temperature reaches 41°C, then there is a higher chance of occurrence of heat stroke that may result death of miner if not treated on time (Brake and

Bates 2002a; ACGIH 2019). Working in high heat zone can cause malfunctioning of nerve and muscle, loss of concentration, which ultimately result in productivity loss and increased rate of heat related accidents (Zhao et al. 2009). Heat stress dominated underground environment causes decrease in productivity and increase in safety and health related issues among miners (Xiaojie et al. 2011; Yi et al. 2019). It has been studied that the human nervous system has a propensity to limit the body activity and the productivity of miners is reduced in heat stress environment (Kocsis and Sunkpal 2017b).

It has been found through a systematic literature review that researchers have proposed several indices to assess the intensity of heat stress in an underground mine environment (Roy et al. 2022). However, a heat stress index that is globally accepted and applicable in all environmental could not be developed yet (Brake and Bates 2002b; Roghanchi et al. 2015). It is also realised that very little effort has been given in predicting heat stress in underground coal mine working places. Considering this as a major research gap, this study focused on the development of an efficient but simple heat stress prediction model for underground coal mines. Prediction of heat stress in underground mine environment will help the mine operators in taking precautionary measures for controlling heat stress and enhancing the health, safety and productivity of the miner.

In this study, an extensive field survey has been conducted to record several mine environmental parameters along with heat stress. Genetic Programming (GP) is done by taking survey data as input to develop a simple relationship between the most sensitive environmental parameters and heat stress. GP is an Artificial Intelligence tool developed by Koza in the year of 1992. The idea of GP came from the Darwinian principle of survival and reproduction of the fittest (Koza 1992). GP has been widely applied in the field of engineering over the last two decades (Hosseini and Nemati 2015). In earth science engineering, GP has been used for prediction of back break in opencast mines (Shirani Faradonbeh et al. 2016; Sharma et al. 2021), fly-rock assessment due to blasting (Faradonbeh et al. 2016), prediction of subsidence due to underground mining (Li et al. 2007), assessing the strength of intact rocks (Asadi et al. 2011), evaluation of deformation modulus of rock mass (Beiki et al. 2010), prediction of tensile and compressive strength of limestone (Baykasoğlu et al. 2008), etc. As far as the knowledge of the authors is concerned, GP has not yet been applied for heat stress prediction in underground coal mines. Hence, authors have realized its wide, versatile and successful application in geosciences, and probably this study is first of its kind that apply GP in the field of heat stress prediction in underground coal mines.

2. Effects Of Heat Stress

Exposure to excessive heat stress is a life-threatening hazard, and some time, it is overlooked to keep the production process unhampered. Maintaining a low heat stress environment puts extra economic burden on operators, so in low to middle income countries workers are highly affected by heat stress (Kjellstrom et al. 2009). There are several sources of heat in underground coal mines which ultimately increase the heat stress among underground coal miners. Some of the important sources of heat include heat released from machinery, heat generated from blasting of explosives, geothermal gradient, auto-compression of air in down cast shaft, oxidation of coal and timber support, human metabolism, etc. (Lazaro and Momayez 2019). When the effective temperature (ET) of surrounding environment exceeds 30°C, the work efficiency of workers starts decreasing (Coco et al. 2016). Safety, productivity and health of the miners are affected due to occupational heat stress (Figure 1).

2.1. Effect on safety

Core body temperature of human is altered due to high heat stress condition. When the core body temperature rises above 38°C, there is chance of malfunctioning of human nervous system. In underground mines, the miners lose their attention while performing work under high heat stress condition. Thereby, the chance of mistake in taking right decision increases, which ultimately aggravates the safety related risks among miners (Xiaojie et al. 2011; Kocsis and Sunkpal 2017a; Belle and Biffi 2018).

Cases due to heat stress hazard in coal producing countries are increasing. In deep underground mines of Australia, 94.2 miners out of 1000 are victim of heat stress related exhaustion (Donoghue and Bates 2000). Accident rate due to heat stress in underground mines increased by 3.6 times when the temperature of working place increased from 30°C to 34°C (Su et al. 2009). In a South African gold mine it was observed that there was no case of accident due to heat stress at a temperature of 27°C, but as the temperature at working place rose up, the accident rate increased, and at a temperature of 32°C, the accident rate was 450 per thousand miners (Su et al. 2009).

2.2. Effect on productivity

The working efficiency of human reduces when WBGT crosses 33°C (Kjellstrom et al. 2009). Fatigue is developed among miners due to working in heat stress environment. Therefore, human nervous system has a tendency to decrease the activity level, which in turn reduces the productivity. In order to minimize the detrimental effects of heat stress during physical work owing to heat hazard, ACGIH (American Conference of Governmental Industrial Hygienists) suggested threshold limit value (TLV) for acclimatized workers. According to the ACGIH prescribed guidelines, where the WBGT of working environment equals or becomes more than 31.5°C and workers are working at moderate metabolic rate, at such condition, workers should spent maximum of 25% of their scheduled shift in performing work and rest of the period they must take rest (ACGIH 2019). Hence, this in turn will increase in the cost of production. The relationship between the productivity loss and temperature rise in Figure 2 depicts that the productivity loss increases asymptotically with increase in the face WBT.

2.3. Effect on health

Working in high heat stress environment is hazardous for the miners. Heat stress is responsible for several heat related illnesses and premature death (Tawatsupa et al. 2012). A study conducted by Flouris et al. (2018) on the workers typically working under heat stress environment revealed 15% workers affected by kidney disease (Flouris et al. 2018). The Mine Safety and Health Administration (MSHA) has reported 717 cases of heat related injuries in mining sector during 2010-2019 (Lazaro and Momayez 2021). When the body is unable to dissipate the internal heat produced due to human metabolism, then there will be definite increase in core body temperature. Increased core body temperature for a prolonged period can cause malfunctioning of respiratory and nervous system. Fatigue, heat rash, heat syncope, heat cramp, heat exhaustion, decrease of mental capacity, lack of electrolyte in body, dehydration and some chronic diseases are the results of prolonged high temperature exposure (Brake 2001; Shi et al. 2015). Causes and symptoms of most common heat related illness (HRI) are presented in Table 1.

Table 1
Causes and symptoms of most common heat related illnesses

Heat related illness (HRI)	Reason	Symptoms
Heat rash	When human body is subjected to constant exposure of heat and humidity and skin remains wet for prolonged period but sweat evaporation is restricted. It reduces sweat evaporative cooling, resulting heat intolerance.	Appearance of bunch of red blisters or pimples, generally on neck, arms, chest and in such portion of the body which rub together like elbow creases.
Heat Cramp	Depletion of electrolyte in body through heavy sweating. Sudden involuntary contraction of muscle.	Painful cramp in muscle of legs, arms, abdomen etc.
Heat exhaustion	Reduction of circulatory blood volume, failure to replace water lost in sweat.	Headache, nausea, dizziness, high body temperature, weakness and reduced urine output.
Heat syncope	Generally occurs among dehydrated and unacclimatized workers due to inadequate blood supply to brain, resulting loss of sense. May occur in heat stress environment after sudden rising from sitting posture.	Dizziness, headache, weakness, pale skin, etc.
Heat stroke	Life threatening heat related illness, which occurs when thermoregulatory system of human body stops working and core body temperature increases more than 40°C. This situation may cause irreversible damage to brain or other vital organs. If not treated timely then life will be endangered.	Dry skin, confusion, loss of sense, very high body temperature, slurred speech, etc.

3. Methodology

Many researchers have estimated the risk posed by heat stress on underground miners and found that it is hazardous in nature (Mahdevari et al. 2014). Heat stress in an underground location is a function of several independent variables, and it changes sharply with a little change in any independent variable. Due to deployment of high-capacity machines, the daily advancement of mining faces and hence the rate of exposure of hot strata surface increases. Accordingly, the heat stress at newly exposed location will vary. Therefore, prediction of heat stress will provide an early indication of heat stress hazard and enable taking precautionary measures.

Broadly, this study was conducted in three steps. Firstly, the field survey and data collection in underground coal mines were done; secondly, the genetic programming model was developed using the field data as input; and finally, the efficiency of prediction model was evaluated. Three deep underground coal mines extended over large area and deploying high level of mechanisation were selected for this study. A well-structured field survey strategy was framed to collect environmental data from the mines for a period of two months. The field survey data were used as input in the GP model. Through GP modelling the relationship between the input and output variables was established. The efficacy of the developed model was evaluated on the basis of fitness functions. In this study the heat stress was measured in terms of Wet-Bulb Globe Temperature (WBGT), because various renowned occupational health related regulatory bodies like National Institute for Occupational Safety and Health (NIOSH), Occupational Safety and Health (OSHA), American Conference of Governmental Industrial Hygienists (ACGIH), etc. recommended WBGT as a heat stress indicator. The methodology of this study is schematically shown in Figure 3.

4. Site Details And Data Collection

Three underground coal mines, namely Moonidih mine, Shyamsundarpur mine and Churcha mine owned by Bharat Coking Coal Limited (BCCL), Eastern Coalfields Limited (ECL) and South Eastern Coalfields Limited (SECL), respectively were selected for this study. Longwall retreating method with double ending ranging drum (DERD) shearer was under practice in Moonidih mine and bord and pillar method of mining by continuous miner was under practice in other two mines. Underground monitoring stations (MS) were established at 100 m intervals throughout the intake air route of each mine to closely monitor the change in temperature and ventilation conditions inside the mine. Depth of each monitoring station and its distance from the mine entry were recorded. Velocity of air (V), dry-bulb temperature (DBT), wet-bulb temperature (WBT), relative humidity (RH) and heat stress in terms of WBGT were measured in every monitoring station throughout the study period. The air velocity was measured by a vane anemometer, and DBT, WBT and RH were measured with a whirling hygrometer. Handheld wet-bulb globe temperature (WBGT) instrument (M/s Extech, model HT30) was used for the measurement of environmental heat stress condition in underground mines.

The one side distance of mine air route starting from mine entrance to working face is measured 3700 m, 3500 m and 3500 m in Moonidih, Shyamsundarpur and Churcha mine, respectively. Accordingly, 37, 35 and 33 measuring stations were established at 100 m intervals in Moonidih, Shyamsundarpur and Churcha mine, respectively for collection of the environmental data. Air velocity drastically reduced with increase in the length of air route starting from the mine entrance. Air velocity at the mining face of each mine is found to be very sluggish. Among the three mines, the air velocity at mining face in Churcha is measured the lowest of 0.5 m/s. Each mining face are highly humid, which is one of the main reasons of discomfort among workers. The summary of data collected from the mines are presented in Table 2.

Table 2
Details of the physical and environmental parameters of the mines used for the development of GP model

Parameter		Moonidih Mine			Shyamsundarpur Mine			Churcha Mine		
		Range	Mean	SD	Range	Mean	SD	Range	Mean	SD
Input	Length of airway (m)	0-3700	1900	1082.4	0-3500	1800	1024.6	0-3300	1718.7	976.3
	Working depth (m)	0-640	569.2	42.7	0-450	239.7	120.5	0-474	402.1	43.2
	Air velocity (m/s)	1-5.3	3.24	1.25	1-4.4	2.95	1.0	0.5-4	1.85	1.12
	DBT (°C)	32.3-33.45	32.86	0.34	30.5-33.2	31.44	0.69	32.5-34.45	33.36	0.53
	WBT (°C)	29.5-31.3	30.3	0.53	28-33.1	30.5	1.45	29.8-33.05	31.4	0.95
	RH (%)	81.2-85.7	83.5	1.31	76.1-92.5	8367	5.38	81.9-90.7	86.85	2.83
Output	WBGT (°C)	26.8-29.4	28.0	0.75	24.8-31.5	28.2	2.04	28.2-31.3	29.81	0.91

5. Prediction Of Heat Stress By Gp

Heat stress in underground mines depends on various independent variables and the relation between them are non-linear and complex. By knowing that genetic programming has ability to solve complex and non-linear problems, in this study we used GP to predict the heat stress in underground coal mines. GP and genetic algorithm are very similar in nature, while the former acts on tree-based structure, the latter acts on binary system. GP begins with randomly created computer programs which are combination of mathematical functions and variables appropriate for the problem. Crossover and mutation operation is done in GP to get a best tree or relation in which the fitness function is optimal (Asadi et al. 2011). Resulted tree of GP represents the mathematical relation between the parameters, constants and pre-defined functions in Lots of Irritating Superfluous Parentheses (LISP) language. For example, a simple representative output tree of function (A+B) X (C+D) is shown in Figure 4.

In GP, the input and output variables and their connecting mathematical functions are pre-defined in the computer program. The most effective input variables among the pre-defined set are automatically selected to generate finest pattern and the non-related variables are eliminated so that the performance of the program is not reduced. GP is advantageous over other AI tools because coding in GP is much simpler and it takes less time to find a fittest solution. The basic steps of GP include setting up the terminal and functional sets, selection of fitness function, control condition setting for the run and finally fixing a criterion to terminate a run. A sample flowchart of GP is shown in Figure 5.

In this study, genetic programming is performed with the help of Gene Xpro 5.0 software. Total dataset obtained from the field survey is randomly divided into a proportion of 80% and 20%, and used as training and testing data set, respectively. Seven mathematical functions {X, /, +, -, Exp, ^2, ^3} are used in the model to attain maximum R^2 and minimum error between the actual and predicted dependent variables. However, GP model considered 6 mathematical functions {+, -, X, /, Exp, ^2} to attain the maximum R^2 value. The run control settings considered in the GP model are presented in Table 3.

Table 3
Parameters used in GP model

GP parameters	Values
Terminal parameters	L, D, V, RH, DBT, WBT
Fitness function	RMSE
Chromosomes	30
Number of genes	3
Heat size	8
Linkage function	Addition

After inserting the independent and dependent variables as given in Table 2 and selecting the mathematical functions, the following equation is obtained for predicting the heat stress in underground coal mines. The best GP output model in tree structure is shown in Figure 6.

$$WBGT = WBT + \frac{(0.365 + RH)}{DBT} + \frac{L - 5.8061}{D \times DBT} + \frac{Exp(-80.5DBT) - V}{(RH - 80.5) + \frac{WBT}{V}} + \frac{(WBT^2 + D) \times DBT}{(20.93RH - 1.729RH^2)}\ ] \quad (1)$$

6. Sensitivity Analysis

Sensitivity analysis is vital to know the importance of input variables on the output variable. By knowing the most significant input variable, it will be easy to effectively deal with the heat stress with least effort. In this study Cosine amplitude method is used to determine the sensitivity of each input variable on the output, and its mathematical expression is given in Equation 2 (Shirani Faradonbeh et al. 2016; Sharma et al. 2021).

$$R_{ij} = \frac{\sum_{k=1}^{n}(x_{ik} \times x_{jk})}{\sqrt{\sum_{k=1}^{n} x_{ik}^2 \times \sum_{k=1}^{n} x_{jk}^2}}$$

2

where,

R_{ij} = sensitivity of an input variable

x_i = input variable

x_j= output variable

n= number of dataset

The impact of each input variable (listed in Table 2) on heat stress (WBGT) is graphically shown in Figure 7. The results of sensitivity analysis depict that DBT has the highest importance (0.98) on the heat stress, followed by WBT (0.97), RH (0.96), depth of working (0.93), air velocity (0.88), and length of mine airway (0.88). DBT covers the maximum amount of heat released by different sources, like heat released by machineries, human metabolism, oxidation of coal and carbonaceous materials, etc. Hence, the sensitivity analysis results seem to be correct in all respect.

7. Results And Discussion

Heat stress is developed within underground coal miners while working under high heat and humid mine environment. It has posed a hazard to the coal miners as it may cause chronic heat related illness and even may cause loss of lives if not treated in time. Prior estimation of heat stress is of great importance to eliminate the heat stress hazard from underground mines. Keeping this in mind, a heat stress prediction model for underground coal mines is developed with the help of genetic programming. Field studies were conducted in three underground coal mines to gather environmental data and use further as input parameters in GP. Field study data indicated that the underground working faces are not comfortable for the miners because of high humidity, low air velocity and high thermal stress. Though the air velocity and quantity at the mine entrance are high, they got reduced as they passed through the mine galleries due to leakage between the intake and return air route. The air velocity at the working face of surveyed mines is measured as low as 0.5 m/s. The other environmental parameters, viz. DBT, WBT and RH increased along with the increase in depth and length of the mine, because of addition of heat from strata, machineries, auto compression of air, presence of strata water, water sprinkling at working places, etc. The WBGT at each mine's working face is on the higher side, i.e., measured 29.4°C, 31.5°C and 31.3°C in Moonidih mine, Churcha mine and Shyamsundarpur mine, respectively. These temperature values are more than the ACGIH prescribed threshold limit of 28°C for continuous working at a moderate metabolic rate (ACGIH 2019).

In this study a non-linear regression technique (GP) is used to predict the heat stress in underground coal mines. The developed genetic programming model is capable of predicting the heat stress at any location in underground mine environment efficiently. The performance of GP model is evaluated by calculating the statistical performance indicators like correlation coefficient (R), coefficient of determination (R^2) and root mean square error (RMSE) (Table 4). The coefficient of determination (R^2) between the actual and predicted heat stress (WBGT) by applying genetic programming on training and testing data set are obtained 0.9637 and 0.9552, respectively (Figures 8 and 9). Hence, it can be concluded that the equation developed by GP model can be effectively used to predict the heat stress (WBGT) in underground mines.

Table 4
Performance indicator of GP model

Performance indicator	Training data set	Testing data set
Correlation coefficient (R)	0.9816	0.9773
Coefficient of determination (R^2)	0.9637	0.9552
Root mean square error (RMSE)	±0.29°C	±0.33°C

The sensitivity analysis by Cosine amplitude method reveled that all the considered independent variables have high impact on the dependent variable (WBGT), and their sensitivity weightage ranged from 0.88 to 0.98. It also revealed that the most sensitive parameter which effects the heat stress is DBT. Hence, the heat stress in underground mines can be effectively controlled by controlling the DBT.

8. Conclusions

In this study an attempt has been made to establish a simple model for predicting the heat stress in underground mine locations. A widely used artificial intelligence tool, namely genetic programming (GP), is applied to predict the heat stress (WBGT) in underground mine environment. Six geo-mining parameters were considered as input variables in the GP. Heat stress predicted by GP has been compared with the actually measured heat stress of the mines. The following inferences have been drawn from this study:

- Heat stress in underground coal mine can be predicted using the equation developed by genetic programming (GP). Correlation coefficient (R) between the GP predicted and actually measured heat stress in training and testing data set is obtained 0.9816 and 0.9773, respectively.
- Sensitivity analysis based on Cosine amplitude method reveled that all six input variables have substantial impact on the output variable, i.e., heat stress. Among the six input variables, DBT has the highest impact (0.98) on heat stress.
- The air velocity at working face of the studied mines is found to be very sluggish. The air velocity at the working face of both Moonidih mine and Shyamsundarpur mine was measured 1 m/s, and in Churcha mine it was measured only 0.5 m/s. This low air velocity is not adequate for replacing the hot and saturated air with fresh unsaturated air, and hence, the heat stress as well as discomfort levels among miners prevailed at the working faces.
- WBGT at the working face of each mine was on the higher side, 29.4°C, 31.5°C and 31.3°C in Moonidih mine, Churcha mine and Shyamsundarpur mine, respectively, which could lead to safety issues, degradation of health, productivity loss, and in turn, increase in production cost.
- Prediction of heat stress (WBGT) at different locations of mine using GP will help in implementation of proper engineering and behavioral/managerial controls to minimize the ill effects of heat stress on miners. Engineering controls like refrigeration of underground ventilation air, shielding heat sources from intake air route to the extent possible, proper ventilation planning, etc. will be beneficial for heat stress control. Moreover, timely water intake, self-spacing, and implementation of work-rest schedule are some

effective behavioral/managerial controls that should be adopted for protecting the mine workers from heat stress.

Declarations

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Competing Interest

The authors have no relevant financial or non-financial interests to disclose.

Authors Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Siddhartha Roy, Devi Prasad Mishra, Ram Madhab Bhattacharjee and Hemant Agrawal. The first draft of the manuscript was written by Siddhartha Roy and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Figures

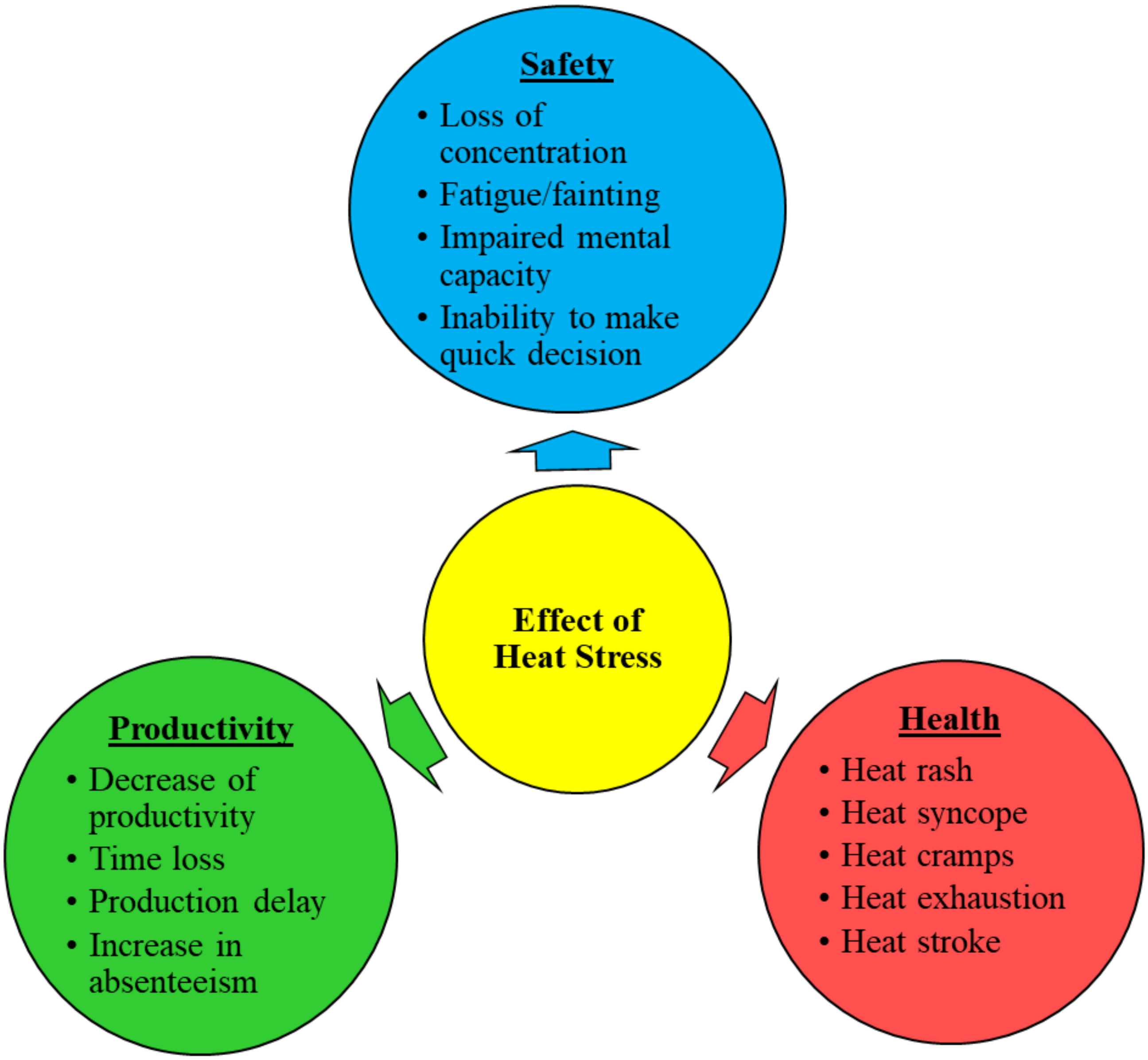

Figure 1

Effects of heat stress

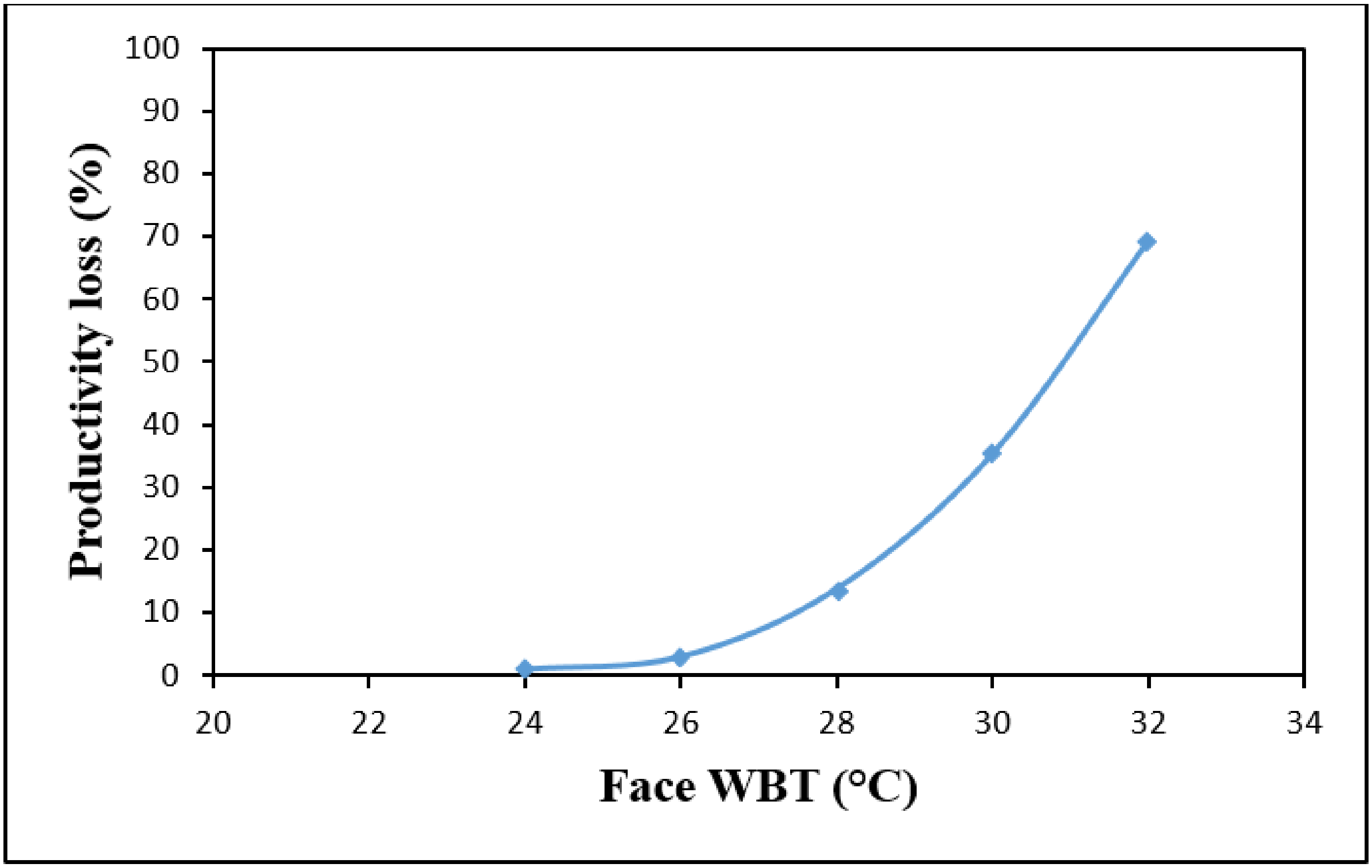

Figure 2

Relationship between WBT and productivity loss (Smith 1984)

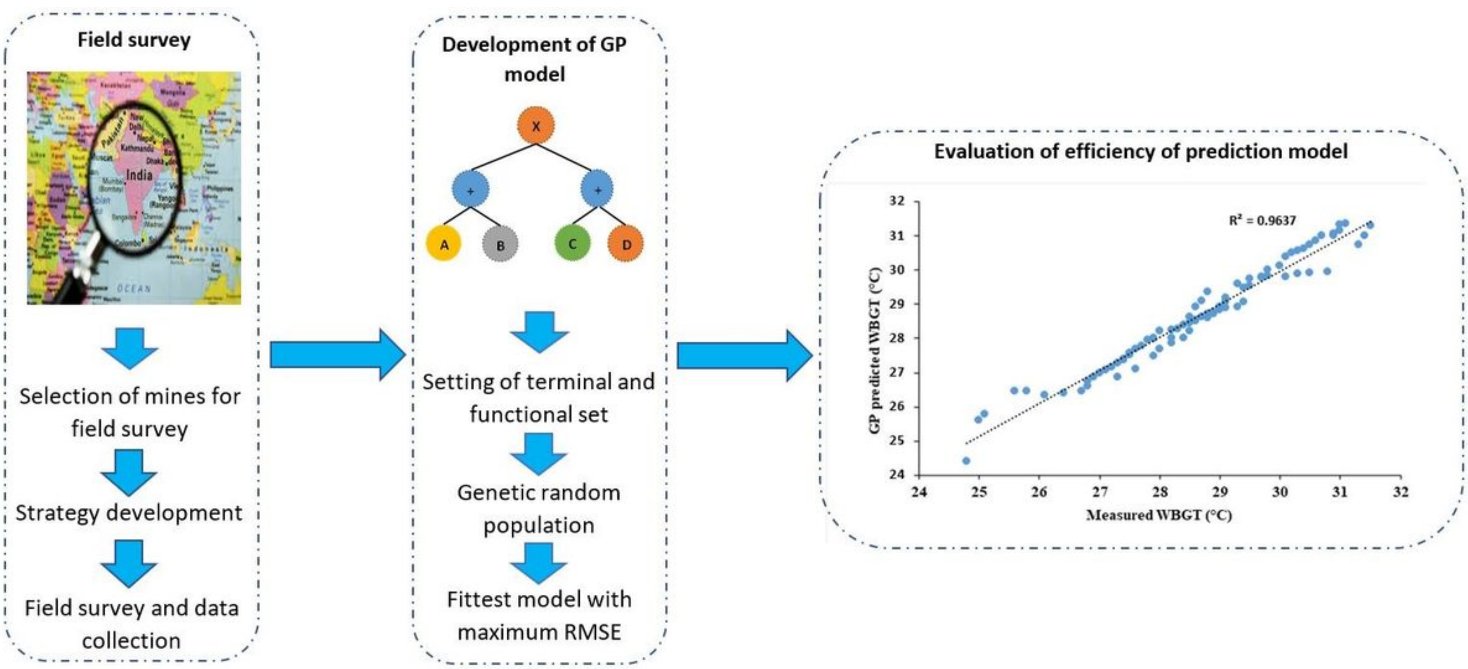

Figure 3

Methodology of the study

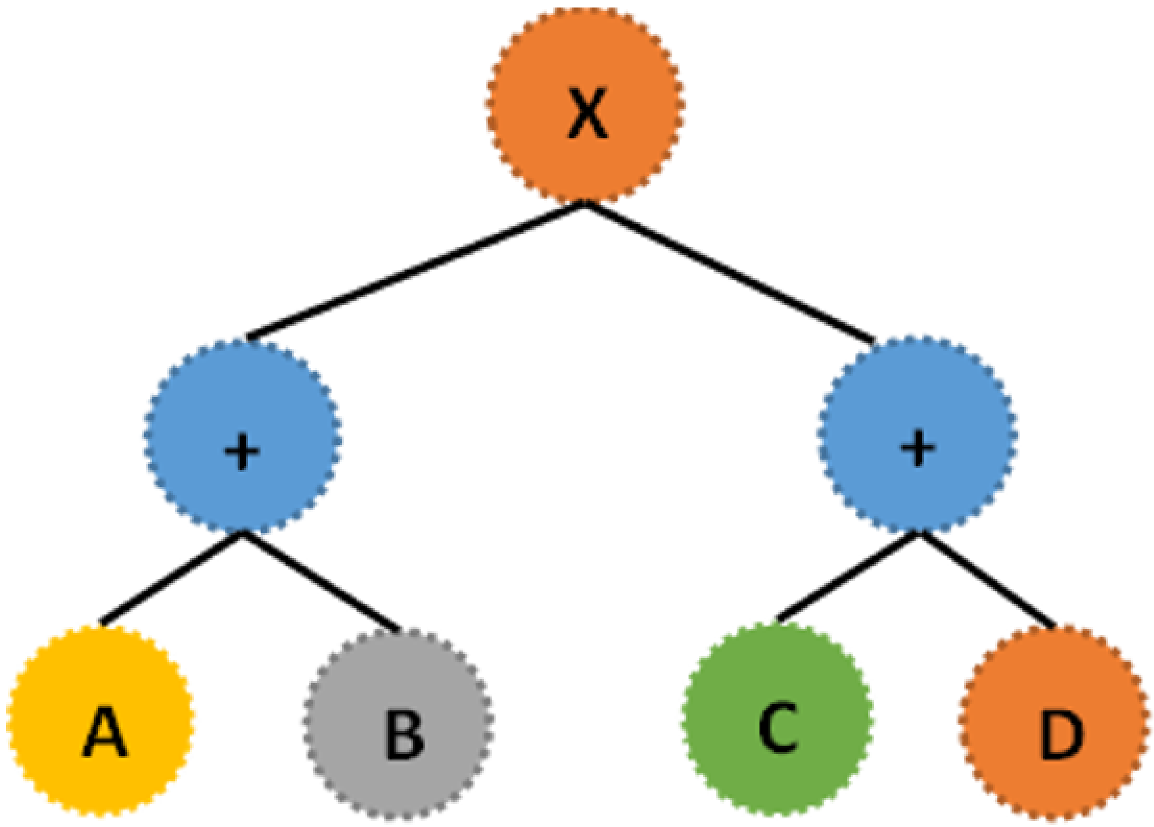

Figure 4

GP tree structure of (A+B) X (C+D).

Figure 5

Sample flowchart of GP

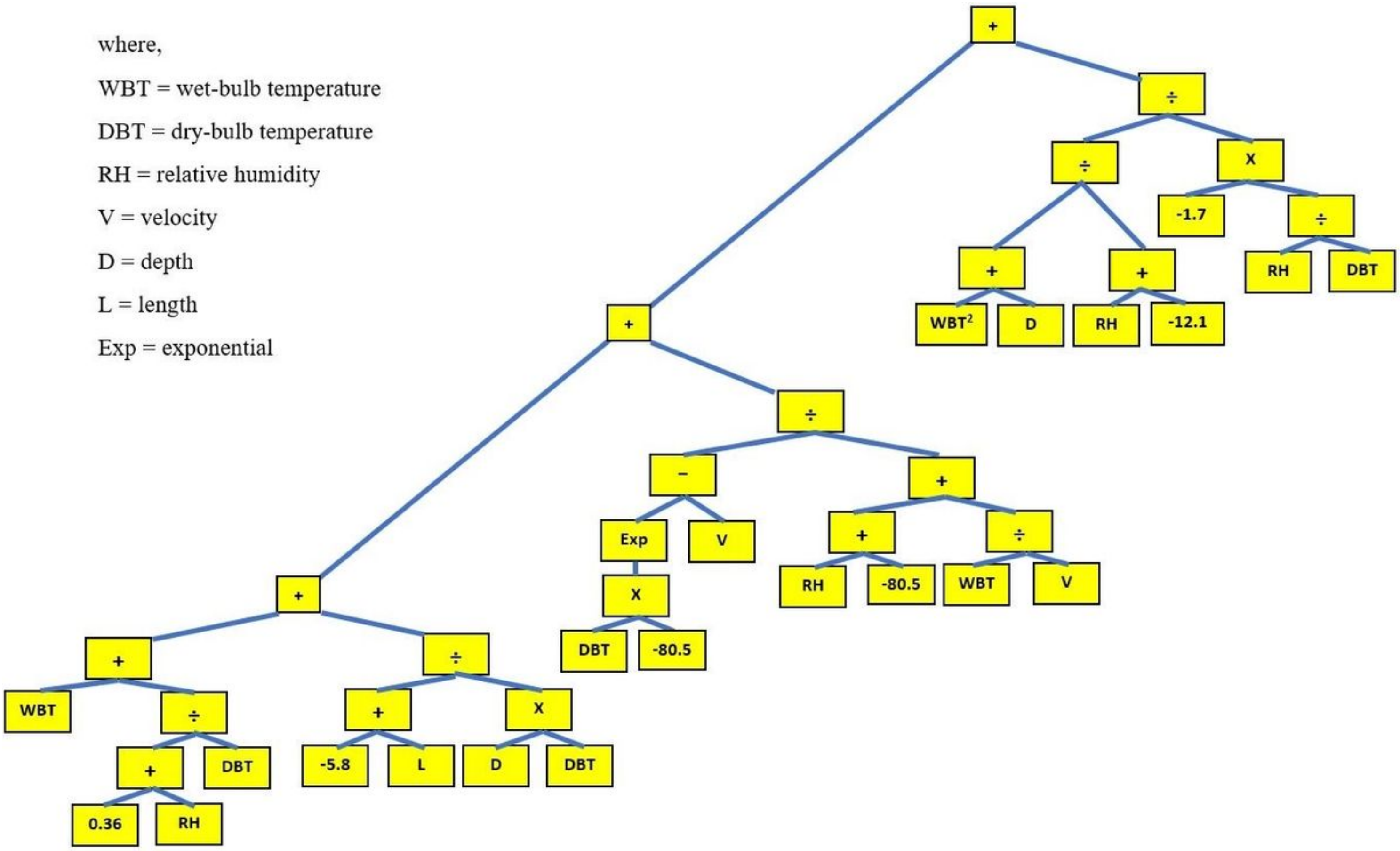

Figure 6

Final expression tree generated by GP

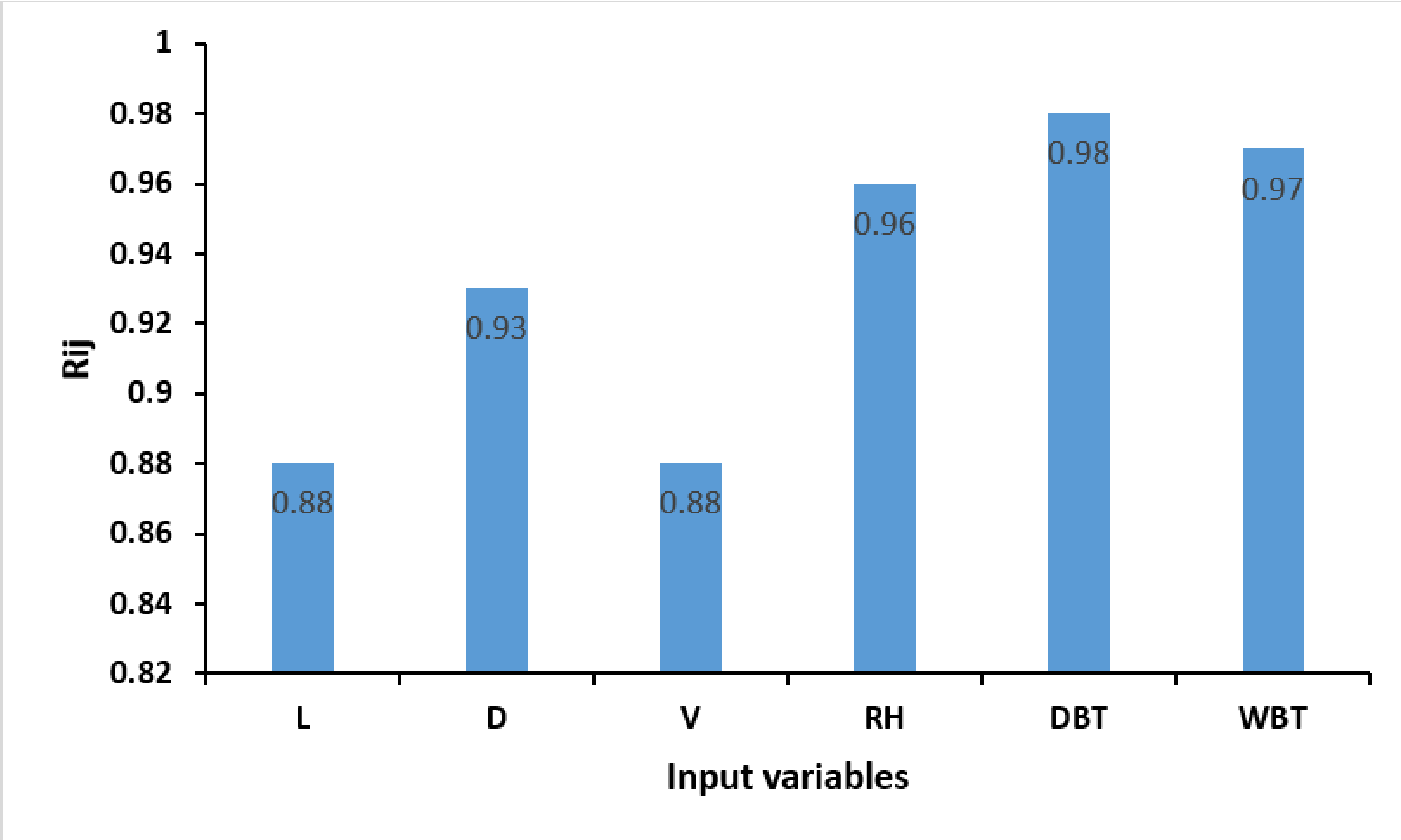

Figure 7

Results of SA obtained applying Cosine amplitude method

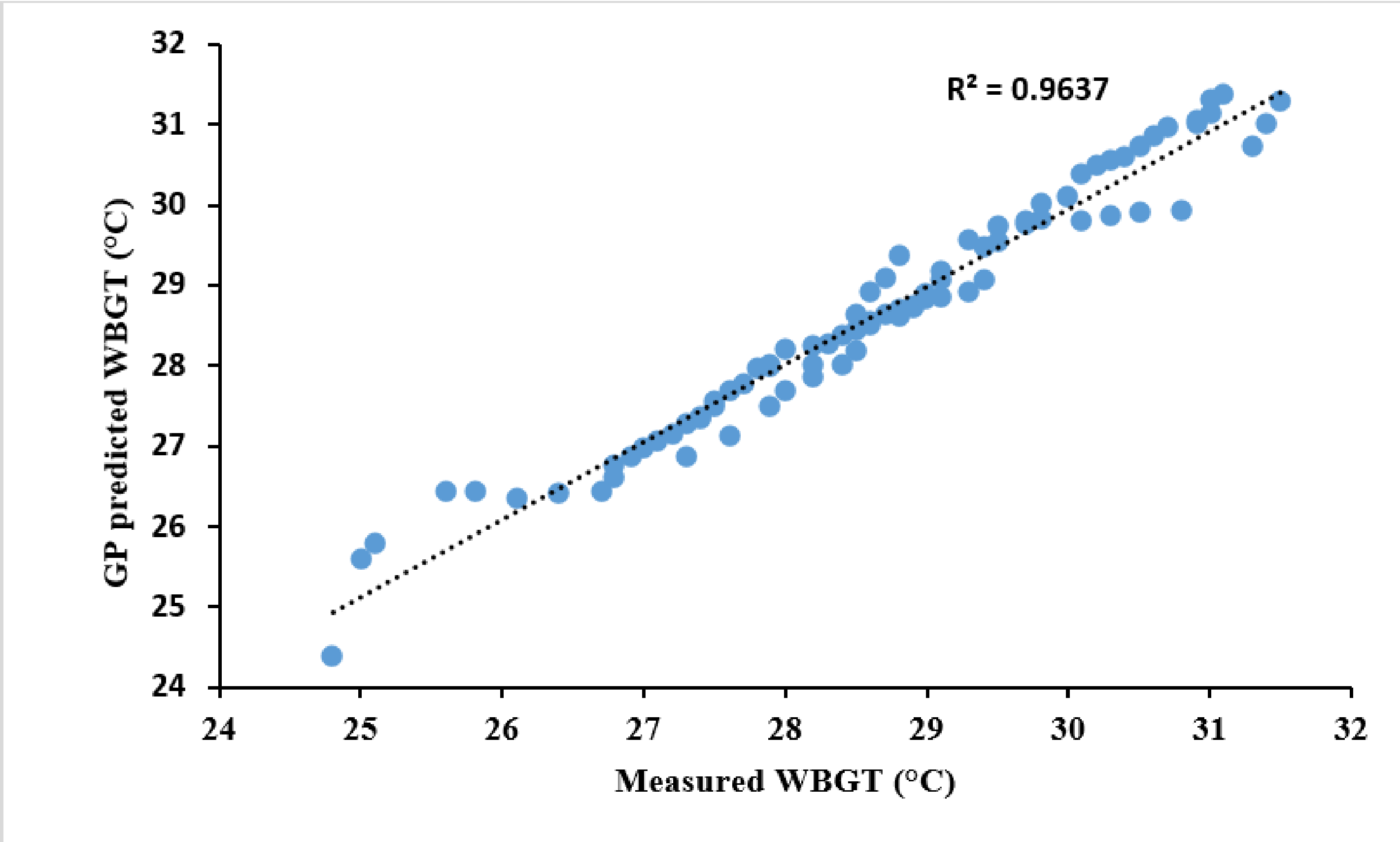

Figure 8

Actual vs predicted WBGT using GP on training dataset

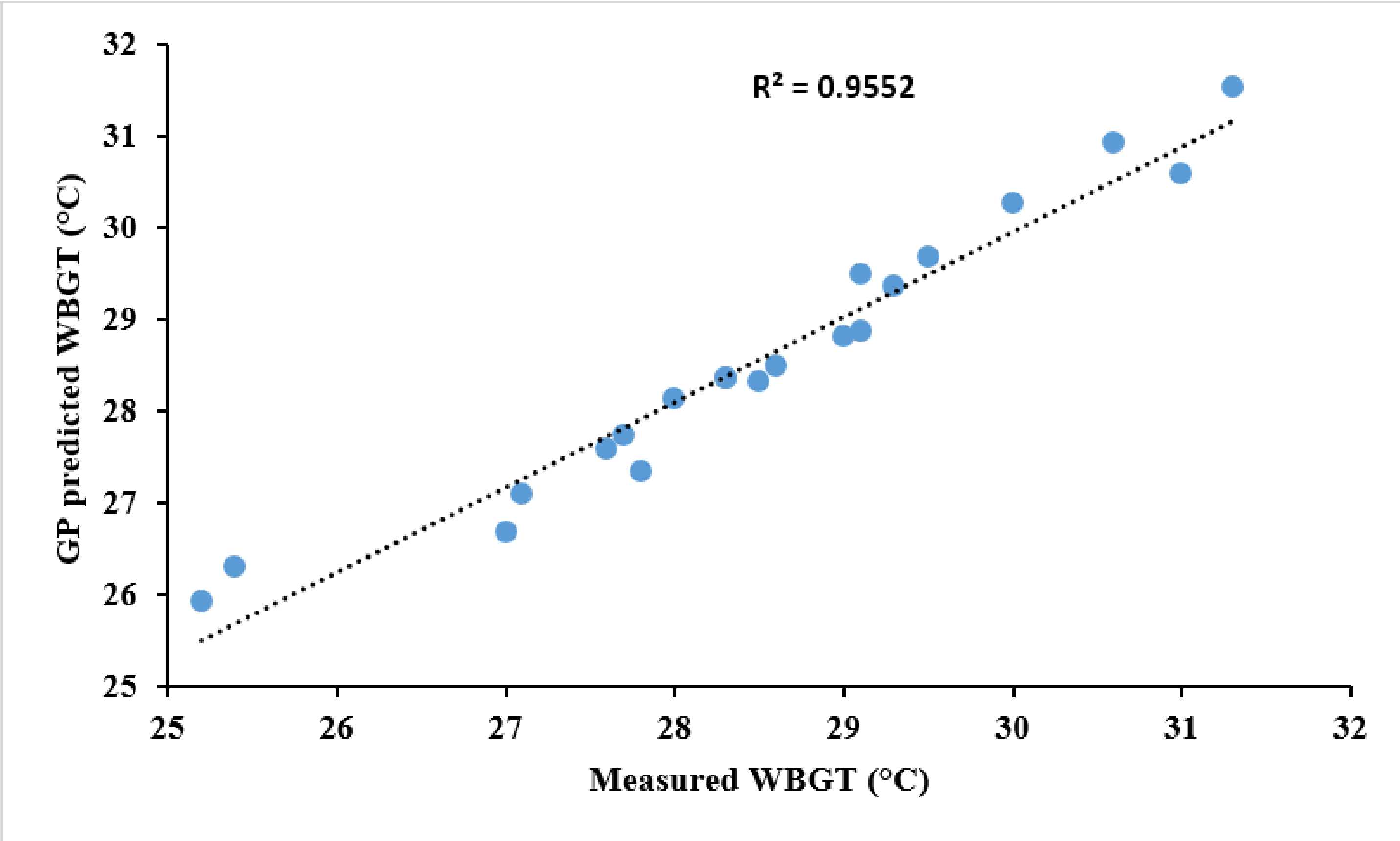

Figure 9

Actual vs predicted WBGT using GP on testing dataset