NUMERICAL TECHNIQUES FOR DIFFERENT THERMAL INSULATION MATERIALS

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ABSTRACT

The objective of this work is to predict the temperature of the different types of walls which are Ferro cement wall, reinforced cement concrete (RCC) wall and two types of cavity walls (combined RCC with Ferrocement and combined two Ferro cement walls) with the help of mathematical modeling. The property of low thermal transmission of small air gap between the constituents of combine materials has been utilized to obtain energy efficient wall section. Ferro cement is a highly versatile form of reinforced concrete made up of wire mesh, sand, water, and cement, which possesses unique qualities of strength and serviceability. The significant intention of the proposed technique is to frame a mathematical modeling with the aid of optimization techniques. Mathematical modeling is done by minimizing the cost and time consumed in the case of extension of the existing work. Mathematical modeling is utilized to predict the temperature of the different wall such as RCC wall, Ferro cement, combined RCC with Ferro cement and combined Ferro cement wall. The different optimization algorithms such as Social Spider Optimization (SSO), Genetic Algorithm (GA) and Group Search Optimization (GSO) are utilized to find the optimal weights α and β of the mathematical modeling. All optimum results demonstrate that the attained error values between the output of the experimental values and the predicted values are closely equal to zero with the SSO model. The results of the proposed work are compared with the existing methods and the minimum errors with SSO algorithm for the case of two combined RCC wall was found to be less than 2%.

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1. INTRODUCTION

A well insulated home reduces energy bills by keeping the room warmer in the winter and cooler in the summer. Insulation acts as a barrier to heat loss and heat gain, particularly in roofs and ceilings and walls.The thermal insulation materials play an important role in achieving building's energy efficiency. Many kinds of thermal insulation materials in buildings are available. Among all, as environment-friendly and renewable materials, natural materials have numerous advantages over other materials and thus arethe most promising for building [1]. Developing new type thermal insulation material become a major trend in the development of thermal insulation materials. Among them, aerogel is one of the most promising new-type high efficient thermal insulation material [2]. Thermal insulation materials have an important role and their use is a logical first step to reducing the energy required to keep a good interior temperature and therefore achieve energy efficiency [3]. The effective thermal resistivity of insulation materials reduces with temperature and moisture content increasing and, consequently it increases the thermal losses of building [4]. The thermal conductivity of insulation materials is greatly affected by their operating temperature and moisture content, yet limited in format ion is available on the performance of insulation materials when subjected to actual climatic conditions [5]. Thermal transmittance can be also estimated through ISO 6946 calculation method, but several comparative studies demonstrated that the calculated U-values is usually lower than the measured ones [6]. The widely used organic thermal insulation materials at present are flammable andlots of hazards have been caused especially when considering the fact that thermal insulation materials have side effects from the stage of their production until the end of their useful lifetime [7]. To achieve the highest possible thermal insulation resistance, new insulation materials and solutions with low thermal conductivity values have been and are being developed, in addition to using the current traditional insulation materials in ever increasing thicknesses in the building envelopes [8]. To protect ecological environment and reduce energy consumption for building, a lot of attention is being paid to develop the environment-friendly and energy-efficient building materials [9]. In addition, reducing emissions through insulation provides a cost-effective measure to combat climate change, reduces energy consumption and therefore reduces Europe's dependence on foreign energy supplies, and creates value-added jobs in Europe [10].

Dixit *et al.* [11] studied the performance of various types of walls such as the Ferro cement wall, the Reinforced Cement Concrete (RCC) wall, and three other types of Cavity walls with different thickness and applied temperature. They carried out an extensive study on the mathematical modeling of designing the objective function (fs) found centered on the evaluation of the output parameter. Several optimization techniques were effectively employed to ascertain the optimal weight of the system. From the evaluation, the average was 96.8% in the overall process and the Group Search Optimization(GSO) algorithm showed the enhanced performance.Effects of the variation of physical and geometrical properties of the urban fabric (i.e. cool roofs including green and white roofs and perviousness of paving materials) on the urban micro-climate and outdoor thermal comfort were investigated using 3dimentional urban micro-climate model, ENVI-met [12]. Based on the predicted results, increasing the amount of vegetation and permeable pavements can cool the air temperature down by up to 3 K.

2. PROPOSED METHODOLOGY

The objective of this work is to predict the temperature of the different types of walls which are Ferro cement wall, reinforced cement concrete (RCC) wall and two types of cavity walls (combined RCC with Ferrocement and combined two Ferro cement walls) with the help of mathematical modeling. The recognized inputs are area of the wall, thickness, time and testing temperature. The heat transferthrough the walls can be lowered significantly with the usage of thermally insulated construction materials. During real time testing, the associated time period may be very large. But the utilization of mathematical modeling with optimization technique can bring about the reduction in the time interval to a great extent. Whereas in the preparation of the methodology 80% of the data set is employed for training function and the remaining 20% of the data set is utilized for the purpose of authentication of the scientific model. The mathematical modeling with Optimization comes out with excellent results by ushering in the optimal weight α and β. Several optimization techniques which are Social Spider Optimization (SSO), Genetic Algorithm (GA) and Group Search Optimization (GSO) are effectively employed to ascertain the optimal weight of the system. The optimal values are based on the minimization of the error and prediction of the temperature of the different walls. The proposed work was compared with the existing work in the literature to improve the error accuracy. It is worth mentioning that the entire work was implemented with the help of MATLAB 2014 software.

2.1 Mathematical modeling

In the mathematical modeling, the identified input and output datasets are employed to train the model for locating the optimal output equation of the innovative technique. At the outset, arbitrary weights α and β are allocated in the network within a specific range. When the preparation of the data set is complete, it is in the range of 80:20 for training and testing purpose respectively. In the mathematical modeling the optimization methods are employed to evaluate the optimal weight α and β of the system for reducing the inaccuracy value of the model. Several optimization techniques are effectively employed to ascertain the optimal weight of the system in which the optimal weight is achieved in the SSO modeling. The data sets are managed by the system for achieving the base slip by utilizing the weights α and β, which are modified for ascertaining the output of the input parameters. In the mathematical modeling, which is generally dependent on various optimizations of the weights, the identified inputs with the optimal weights are taken as per equation (2).

2.2 Social spider optimization (SSO)

The SSO assumes that entire search space is a communal web, where all the social-spiders interact with each other. In the proposed approach, each solution within the search space represents a spider position in the communal web. Every spider receives a weight according to the fitness value of the solution that is symbolized by the social-spider.The procedure for SSO process is shown below as Pseudo code.

2.2.1 Initialization

Initialize the input parameters such as weight α and β which is defined as the α_i, β_i is an initial solution of spider and i is a number of solutions and also initialize the parameters such as step,this process is known as initialization process.

$$S_i = \{S_{0j}, S_{1j}, \ldots S_{nj}\}$$

where, S_i defines an initial solution, $i = [1, 2, \ldots 10]$ and $j = [1, 2, \ldots 140]$. Since, i^{th} value is considered as the number of solution and j^{th} value is considered as length of solution.

$$S_i = \begin{bmatrix} (No \ of \ hidden \ neuron * No \ of \ input \ data) + \\ \\ No \ of \ hidden \ neuron \end{bmatrix} \tag{1}$$

Here Total input = 4; Hidden neuron $(h) = 20$

Based on equation (1), the attained solution length is 140 and the solution range lies between $-10 \leq S_{ij} \leq 10$. The input data which are area, thickness, testing temperature and time. According to the initial solution based on wall temperature is evaluated.

2.2.2 Fitness function

Evaluate the fitness value of each solution and then calculate the best solution values.

$$F_i = \sum_{j=1}^{h} \alpha_j * \left(\frac{1}{1 + \exp(-\sum_{i=1}^{N} S_i \beta_{ij})} \right) \tag{2}$$

where, F_i is a fitness function, α and β are weights, S is the input parameters, i is the number of inputs; j is the number of weights and h is the number of hidden neurons.

2.2.3 New population updation by using following procedure

The algorithm models two different search agents (spiders): males and females. Depending on gender, each individual is conducted by a set of different evolutionary operators which mimic different cooperative behaviors that are commonly assumed within the colony. Considering N as the total number of n-dimensional colony members, define the number of male N_m and females N_f spiders in the entire population S.

$$N_f = floor[0.9 - rand.025).N] \quad and \quad N_m = N - N_f \tag{3}$$

where rand is a random number between [0, 1] and floor (.) maps a real number to an integer number.

2.2.4 Weight assignation

In the biological metaphor, the spider size is the characteristic that evaluates the individual capacity to perform better over its assigned tasks. Every individual (spider) receives a weight w_i which represents the solution quality that corresponds to the spider i (irrespective of gender) of the population S. Calculate the weight of every spider of S using equation (4).

$$w_i = \frac{F(s_i) - worst_S}{best_s - worst_s} \tag{4}$$

where $F(s_i)$ is the fitness value obtained by the evaluation of the spider position s_i with regard to the objective function F .The values $worst_s$ and $best_s$ are calculated using the following equation.

$$best_s = \min_{k=\{1,2,...N\}} (F(s_k)) \, and \quad worst_s = \max_{k=\{1,2,...N\}} (F(s_k)) \tag{5}$$

2.2.5 Fitness based initializes the population

The algorithm begins by initializing the set S of N spider positions each spider position f_i and m_i is a n dimensional vector containing the parameter values to be optimized. Such values are randomly and uniformly distributed between the pre specified lower initial parameter bound p_j^{low} and the upper initial parameter bound p_j^{high} by using equation(6) and (7).

$$f_{i,j}^0 = p_j^{low} + rand(0,1).(p_j^{high} - p_j^{low}) \qquad (i = 1,2...N_m, j = 1,2,..n) \tag{6}$$

$$m_{k,j}^0 = p_j^{low} + rand(0,1).(p_j^{high} - p_j^{low}) \quad (k = 1,2...N_m, j = 1,2,..n) \tag{7}$$

where i, j and k are the parameter and individual indexes respectively, whereas zero signals the initial population, Hence $f_{i,j}$ is the *jth* parameter of the *ith* female spider position.

2.2.6 Cooperative operators

2.2.6.1 Female cooperative operator

Female spiders present an attraction or dislike over others irrespective of gender. For a particular female spider, such attraction or dislike is commonly developed over other spiders

according to their vibrations which are emitted over the communal web. Since vibrations depend on the weight and distance of the members which have originated them, strong vibrations are produced either by big spiders or other neighboring members lying nearby the individual which is perceiving them. The first one involves the change in regard to the nearest member to i that holds a higher weight and produces the vibration $Vibc_i$. The second one considers the change regarding the best individual of the entire population S who produces the vibration $Vibb_i$. The female vibration $Vibc_i$ and $Vibb_i$ are calculated by using equation (8).

$$Vibc_i = w_c.e^{-d_{i,c}^2} \quad Vibb_i = w_b.e^{-d_{i,b}^2} \tag{8}$$

The Vibration $Vibc_i$ are perceived by the individual $i(s_i)$ as a result of the information transmitted by the member $c(s_c)$ who is an individual that has two important characteristics: it is the nearest member to i and possesses a higher weight in comparison to $i(w_c > w_i)$. The Vibration $Vibb_i$ are perceived by the individual i as a result of the information transmitted by the member $b(s_b)$ with b being the individual holding the best weight of the entire population S such that $w_b = \max_{k \in \{1,2,...N\}} w(k)$.

If rm is smaller than threshold PF an attraction movement is generated; otherwise a repulsion movement is produced. Therefore, such operator can be modeled as follows:

$$f_i^{k+1} = \begin{cases} f_i^k + \alpha.Vibc_i.(s_c - f_i^k) + \beta.Vibb_i.(s_b - f_i^k) + \delta.(rand - \tfrac{1}{2}) \, with \quad proability \, PF \\ f_i^k - \alpha.Vibc_i.(s_c - f_i^k) + \beta.Vibb_i.(s_b - f_i^k) + \delta.(rand - \tfrac{1}{2}) \, with \quad proability \, 1-PF \end{cases} \tag{9}$$

where α, β, δ and $rand$ are random numbers between [0, 1] whereas k represents the iteration number. The individual s_c and s_b represent the nearest member to i that holds a higher weight and the best individual of the entire population S.

2.2.6.2 Male cooperative operator

Male members, with a weight value above the median value within the male population, are considered the dominant individuals D. On the other hand, those under the median value are labeled as non-dominant ND males. In order to implement such computation, the male population $M(M = \{m_1, m_2,...m_{N_m}\})$ is arranged according to their weight value in decreasing order. Thus, the individual whose weight $w_{N_{f+m}}$ is located in the middle is considered the median male member the vibration of the male $Vibf_i$ calculated by using equation (10). The Vibration $Vibf_i$ perceived by the individual $i(s_i)$ as a result of the information transmitted by the member $f(s_f)$ with f being the nearest female individual to i.

$$Vibf_i = w_f . e^{-d_{i,f}^2} \tag{10}$$

Since indexes of the male population M in regard to the entire population S are increased by the number of female members N_f, the median weight is indexed by N_{f+m}. According to this, change of positions for the male spider can be modeled as follows.

$$m_i^{k+1} = \begin{cases} m_i^k + \alpha.Vibf_i.(s_f - m_i^k) + \delta.(rand - \frac{1}{2}) if & w_{N_{f+i}} > w_{N_{f+m}} \\ m_i^k + \alpha. \left(\dfrac{\sum_{h=1}^{N_m} m_h^k . w_{N_{f+h}}}{\sum_{h=1}^{N_m} w_{N_{f+h}}} - m_i^k \right) if & w_{N_{f+i}} \le w_{N_{f+m}} \end{cases} \tag{11}$$

where the individual s_f represents the nearest female individual to the male member i whereas

$\left(\dfrac{\sum_{h=1}^{N_m} m_h^k . w_{N_{f+h}}}{\sum_{h=1}^{N_m} w_{N_{f+h}}} \right)$ corresponds to the weighted mean of the male population M .

By using this operator, two different behaviors are produced. First, the set D of particles is attracted to others in order to provoke mating. Such behavior allows incorporating diversity into the population. Second, the set ND of particles is attracted to the weighted mean of the male population M. This fact is used to partially control the search process according to the average performance of a subgroup of the population.

2.2.7 Mating process

Mating in a social-spider colony is performed by dominant males and the female members. Under such circumstances, when a dominant male m_g spider ($g \in D$)locates a set E^g of female members within a specific range r(range of mating), it mates, forming a new brood s_{new} which is generated considering all the elements of the set T^g that, in turn, has been generated by the union $E^g \cup m_g$. It is important to emphasize that if the set E^g is empty, the mating operation is canceled. The range r is defined as a radius which depends on the size of the search space. Initialize randomly the female $(F = \{f_1, f_2, ... f_{N_f}\})$ and male $(M = \{m_1, m_2, ... m_{N_m}\})$ where $S = \{S_1 = f_1 S_2 = f_2 ...... S_{N_f} = f_{N_f}, S_{N_{f+1}} = m_1, S_{N_{f+2}} = m_2 ... S_N = m_{N_m}\}$ and calculate the radius mating.

$$r = \frac{\sum_{j=1}^{n} (p_j^{high} - p_j^{low})}{2.n} \tag{12}$$

In the mating process, the weight of each involved spider (elements of T^g) defines the probability of influence for each individual into the new brood. The spiders holding a heavier weight are more likely to influence the new product, while elements with lighter weight have a lower probability. The influence probability P_{si} of each member is assigned

by the roulette method, which is defined as follows;

$$p_{si} = \frac{w_i}{\sum\limits_{j \in T^k} w_j} \qquad where \quad i \in T^g \tag{13}$$

Once the new spider is formed, it is compared to the new spider candidate s_{new} holding the worst spider s_{wo} of the colony, according to their weight values. If the new spider is better than the worst spider, the worst spider is replaced by the new one. Otherwise, the new spider is discarded and the population does not suffer changes. In case of replacement, the new spider assumes the gender and index from the replaced spider. Such fact assures that the entire population S maintains the original rate between female and male members. These process based find the optimum hidden layer and neuron of the neural network process.

2.2.8 Optimal solution

Based on the above mentioned procedure the process attains the optimal weights and also find the optimal fitness which is defined as $F_{optimal}$ in this optimal fitness based find the output. The optimal equation is based on prediction of the output temperature of the wall.

$$F_{i(optimal)} = \sum_{j=1}^{h} \alpha_{j(optimal)} * \left(\frac{1}{1 + \exp(-\sum\limits_{i=1}^{N} S_i \beta_{ij(optimal)})} \right) \tag{14}$$

where, α and β are weights range from -500 to 500, S is the input parameters, i is the number of inputs, j is the number of weights and h is the number of hidden neurons. Then the error value is found by using equation (15).

$$E_i = \sqrt{\frac{\sum\limits_{i=1}^{ND} (D_i - P_i)^2}{ND}} \tag{15}$$

where ND is the number of the data, D is the desired value and P is the predicted value, i= 1,2,….n. By using this formula, the error value is obtained from the difference between desired value and predicted value.

3. RESULT AND DISCUSSION

In this study, the parameters such as thickness of wall, applied temperature, area and time are considered for the analysis of temperatureof Ferro cement wall, RCC wall, combination of Ferro cement and RCC wall and combination of two Ferro cement wall. The mathematical modeling using SSO elegantly performs the fascinating function of finding the

optimal solutions of α and β.

Subsequently, the optimal solutions of the weights with input constraints are arrived at with the assistance of the SSO process. The output is modified for the least error value by the mathematical model. In other words the differential error between realtime output and the attained output from the mathmatical model is found to be nearly equal to zero.With the result, the related output is evaluated by utilizing the temperature of the different walls.

3.1 Convergence graph

Fig. 1 shows the average fitness graph for the thermal insulation material based on the iteration of the SSO and GA by altering the weights in the range of -500 to 500, and thus the error values are determined. The error graph is drawn with the iteration along the X-axis and fitness along the Y–axis.

The minimum fitness value that is error value is attained in 100th iteration.Initial error value of the SSO and GA process is 318 and the objective function of the algorithm is based on minimizing the error values. From the convergence graph it can be seen that the SSO approach obviously specifies the ideal fitness value with the competent results.

The GA algorithm reduces the fitness value from 318 to 65 below 20th iteration and remains almost stable up to 88th iteration then reduced the fitness to 5. From the convergence graph it is evident that the SSO approach obviously specifies the ideal fitness value with the competent results.
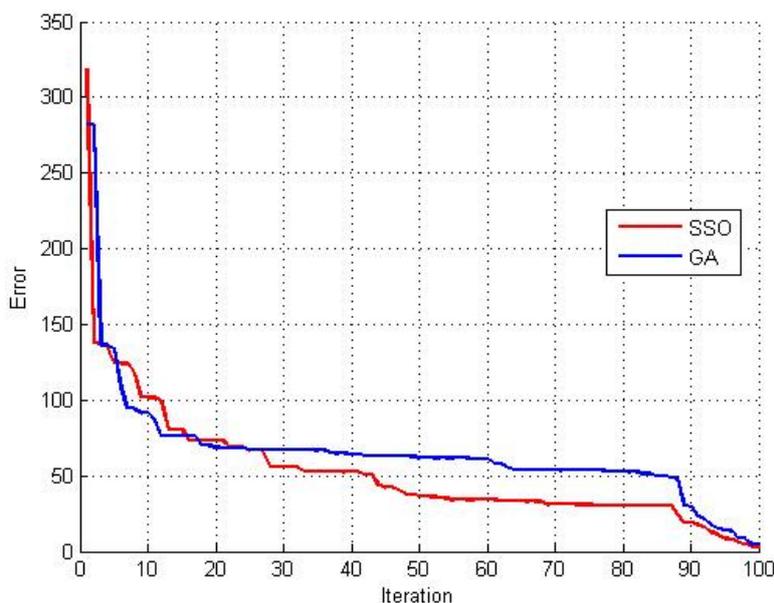

Figure 1. Convergence graph

3.2 Error values of output parameters in different algorithm

The error values of output parameters for different walls in different algorithms which are calculated for the input data such as area, thickness and testing temperature are plotted in Figs. 2-6. The number of data is taken as abscissa and the error value of wall temperature is

taken as the ordinate.

Figs. 2-6 shows the temperature error values for the different walls of different testing data. Fig. 2 shows that the temperature error values for the Ferro cement wall.The minimum error in this process is 0.036 for SSO in initial testing data. This minimum error as compared to the GA the error difference is 98.8 % and as compared to GSO technique the error difference is 92.08 %.
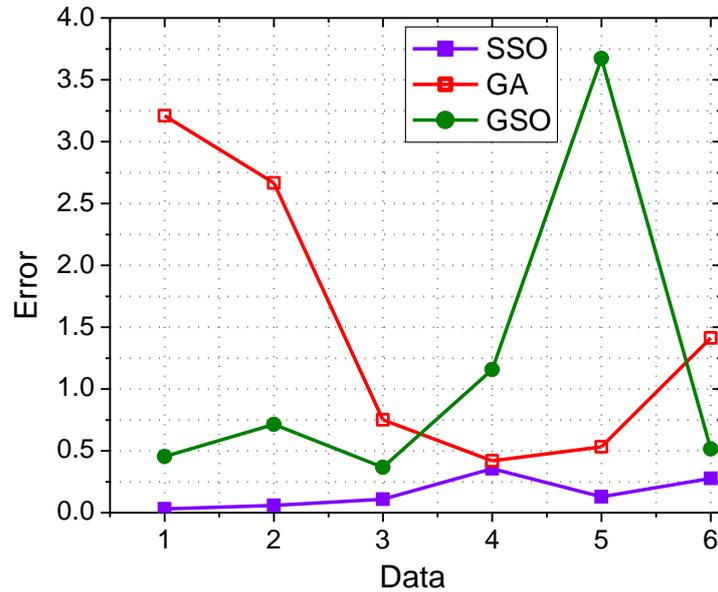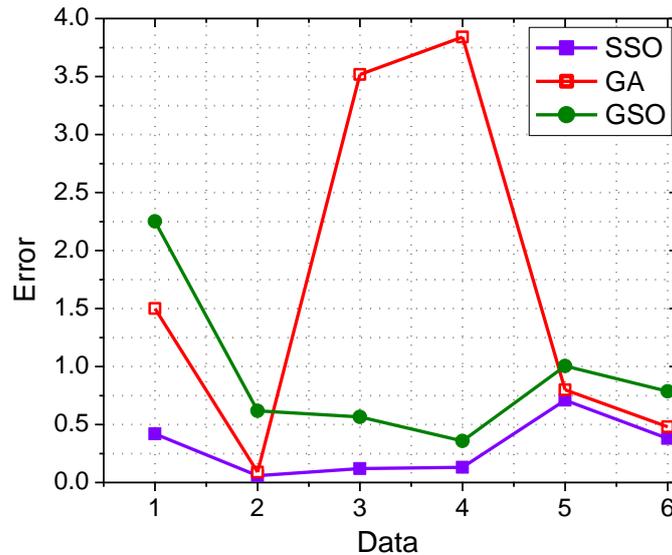

Figure 2. Error graph for ferrocement wall panel

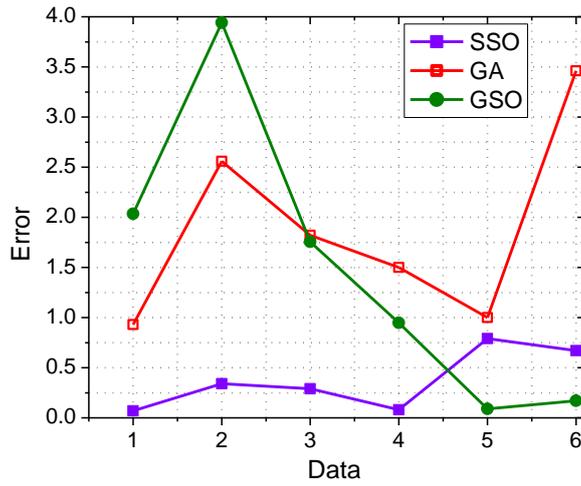Figure 3. Error graph for RCC wall panel

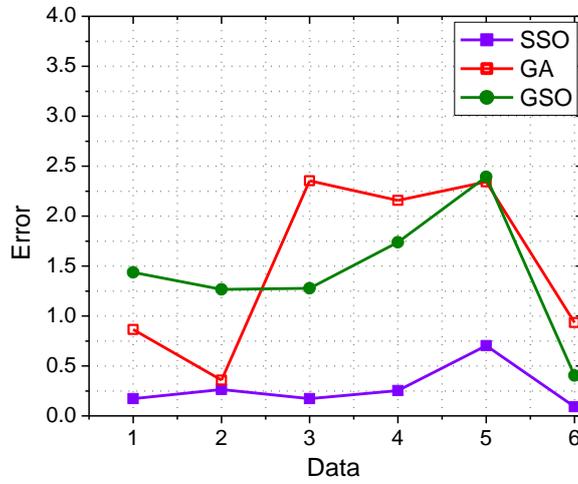Figure 4. Error graph for combined ferrocementand RCC wall panels

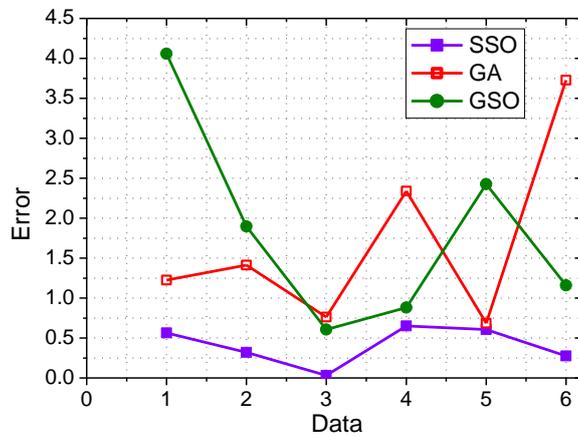Figure 5. Error graph for combined two ferrocement wall panels

Figure 6. Error graph for combined two RCC wall panels

Fig. 3 shows the temperature error value for the RCC wall.The proposed method i.e., SSO methodascompared to GA modeling, the error difference is 85.63%. Fig. 4 shows the error value of the cavity wall (combined RCC and Ferrocement wall).The minimum error is attained in the SSO process.It is compared with the GA optimization technique the error difference is found to be 99.75%. Fig. 5 shows the performance of another cavity wall which is obtained by combining two Ferro cement walls. Fig. 6 shows the temperature error value of two combined RCC wall.The maximum error value of the proposed method is 0.65 in testing data 4.Minimum error value of SSO is 0.033 in 3rdtesting data. The difference of the temperature error value of SSO as compared to the GA the variation is 95.66 % and as compared to GSO the variation is 94.56 %.

3.3 Testing results of different wall panels

Mathematical modeling process consists of two divergent procedures such as the training and testing process. In the training process, 80% of data is precisely used by duly modifying the weightsand the remainder 20% is effectively employed in the testing process. The experimental analysis results and forecasted temperature values based on the optimization technique are presented in form of graphs. The testing results of the mathematical modeling process for the different wallshaving different thermal insulation materials such as Ferro cement, RCC wall and different cavity wallsare obtained based on the area, thickness, time and testing temperature values. The predicted wall the temperature values for different thermal insulation materialsin SSO model matches closely with the experimental data.

3.4 Comparative analysis

The Figs. 2-6 successfully shows the average fitness graph of different optimization processes such as Social Spider Optimization (SSO), Genetic Algorithm (GA) and Group Search Optimization (GSO) for the different walls. Least error value is obtained for the proposed SSO method as compared to theother existing processes such as GA and GSO algorithm.

Fig. 7 Shows the comparison of the error values of different walls for proposed method and existing process.Existing process are the group search optimization (GSO) process and Genetic Algorithm (GA) technique. For the Ferrocement wall the minimum error value in SSO process is 0.999 and similar values are attained for all the walls.The average error difference for all the wall panels of the proposed method and existing method is 96.5%.
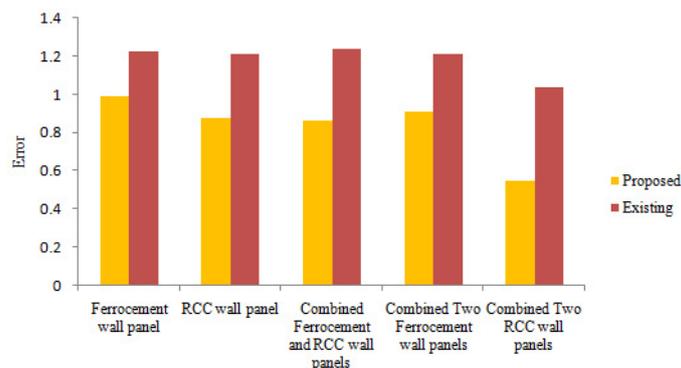

Figure 7. Comparison graph

4. CONCLUSIONS

Social Spider Optimization (SSO) technique gives the accurate ideal values of the weights by optimizing the cost and time consumed as compared to the existing optimization techniques.Mathematical modeling is utilized to predict the temperature ofthe different walls such as RCC wall, Ferro cement wall, combined RCC with Ferro cementwall, two combined Ferro cement walls and two combined RCC walls.The different optimization algorithms such as Social Spider Optimization (SSO), Genetic Algorithm (GA) and Group Search Optimization (GSO) are utilized to find the optimal weights α and β of the mathematical modeling. During the operation of the system the output parameters are assessed with the data sets.All optimum results demonstrate that the attained error valuesbetween the experimental data and the predicted values are closely equal to zero in the SSO model. The minimum errors of mathematical modeling with SSO process in the case of the Ferro cement wall, RCC wall, combined RCC with Ferro cement, combined two Ferro cement wall and combined two RCC walls are found to be less than 2 %.

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