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Estimation of Time and Cost in Prefabrication Construction AID of ANN with SSO

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Abstract: Prefabrication technology (prefab is the practice of assembling components of a structure in a factory or other manufacturing siteand then transporting the assembled components to the construction site where the structure is to be located. The term is used to differentiate between the process of the conventional construction practice, i.e., transporting the basic materials to the construction site. Cost and time savings emerge to be the chief benefits which makes us adopt the new technique. The objective of the research is to enclose an Artificial Neural Network (ANN) with the aid of optimization techniques. In order to predict the time and cost performance parameters of the prefabrication technology process the ANN is utilized. There are different types of optimization techniques such as Grey Wolf Optimization (GWO), Harmony Search (HS) and Social Spider Optimization (SSO) algorithm which are utilized to arrive at the optimal weight of the ANN process. The optimum results demonstrate the attained error values between the output of the experimental values and the predicted values which are closely equal to zero in the designed network. It is gathered from the results that, the minimum error of time performance and cost performance is 81.2 and 76.28% determined by the ANN as attained by the Social Spider Optimization (SSO) algorithm.

Key words: Prefabrication technology, construction, Enterprise Resource Planning (ERP), Artificial Neural Network (ANN), Social Spider Optimization (SSO), India

INTRODUCTION

Fatigue evaluation has gained much significance for the current steel and concrete composite bridges in the domain of civil engineering. The aspect of sustainability is also the reason for it gaining supreme significance in civil engineering constructions, especially for the bridges (Lener *et al*., 2013). Fatigue has not so far resulted in extensive challenges for the typical concrete highway bridges, primarily because of the ratio of dead load to live load least. In certain cases, at least, the traffic loads are not enough to create noteworthy fatigue detrimental stresses in the structural elements (Treacy and Bruhwiler, 2015). The task of safeguarding the highway construction security has paved the way efficiently to avert and manage accidents. This has emerged to be the vital task in the highway construction security management (Wu and Shen, 2012). The process of construction and interdependency between the activities must be specified in order to perform a realistic and suitable simulation. Usually, the process and their interdependency has to be specified manually (Konig *et al*., 2012). In the construction project, tendering and bidding represents the trading technique universally identified and extensively used in allocating or undertaking the engineering tasks. The bid estimation constitutes the fundamental link in biddingand the essence of the overall bidding task (Hong, 2011). All the construction procedures, terms, financing conditions, safety needs, risk management and final outcomes have to be taken into consideration and specifically documented in the construction contract (Trinkuniene and Trinkunas, 2014). Prefabrication of building components at a remote facility is efficient to save space for material storage on site, assures better quality control of part production, reduces wastage and enables reengineered and more efficient supply chain management (Babic *et al*., 2010). Prefabrication can offer significant advantages such as shortened construction time, improved quality, enhanced occupational health and safety, less construction site waste, less environmental emissionsand reduction of energy and water consumption (Chen *et al*., 2010). Performance problems like cost overruns and schedule slippages have been prevalent in the construction industry and have prompted practitioners to explore new approaches in streamlining the design and construction process (Cao *et al*., 2015). The prefabrication of buildings has proved to provide savings in the construction

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wastage of up to 52%, mainly through the minimization of off-cutsand this can significantly improve the energy, cost and time efficiency of construction (Aye *et al*., 2012). For the success of the project not only the design of the final product often called detailed planning is taken into consideration. But the building production also has to be considered during the design process (Berner *et al*., 2013). Implementing lean construction in the construction industry helps to improve sustainability by optimizing resource utilization and human safety during construction activities and minimizing wastage through standard procedures (Nahmens and Ikuma, 2011). Additionally, knowledge of a project's likelihood is necessary to have cost overruns that helps to identify projects to receive increased scrutiny during the construction process to control costs (Williams and Gong, 2014). The evolution of construction technology has led to a rapidly increase in the market for supplying off-site technology and innovative building systems (Pan *et al*., 2012). The construction enterprises are exposed to several risks at the time of execution of the engineering project. The appropriate way to tackle these challenges successfully constitutes a vital issue for sustainable growth in the modern construction enterprises (Zhao *et al*., 2011). In this regard, the enterprise resource planning primarily focuses its attention on successfully facing the business or project ambiguities in a positive way with an eye on reducing the gravity of the challenges, in addition to enhancing the opportunitiesand optimizing the attainment of the related objectives (Kumar and Gupta, 2012). We focus on the mechanics of the cost estimation process and examine its influence on the accuracy of cost estimation for the building (Makovsek, 2014). These objects contain the costs and resources data of the project in detail. As a result, the project schedule and cost estimation are performed separately (Feng *et al*., 2010).

Literature review: Arashpour *et al.* (2015) had proposed that traditional approaches in construction and project management assigned each process to a trade contractor with an individual specialization and trades with the greatest work content (bottlenecks) has a significant influence on the progress rate of projects. One of the chief constraints of optimization problem was the optimal number of additional skills. In order to compare, process integration strategies and use of multi-skilled resources tangible performance metrics of systems were used. Findings have shown that choosing optimal process integration architecture depends on the level of capacity imbalance and processing time variability. This investigation optimizes the decision making involved on process integration in off-site construction networks. Sadowski and Hola (2015) had proposed that when making and repairing concrete floors it is vital to prepare the interlayer bonding surface in proper manner. To assess pull-off adhesion the optical laser triangulation method and the acoustic impulse response method is used, using Artificial Neural Networks (ANN) on the basis of a few parameters (independent of top layer thickness) which is determined by these methods. Relatively high linear correlation coefficients R = 0.8847, 0.8492 and 0.8989 for the training, testing and verification of ANN, respectively with the Quasi-Newton Algorithm, denoted as MLP-QN were obtained. The proposed NDT method of assessing the pull-off adhesion of the top concrete layer to the base concrete layer in floors is independent of top layer thickness. This means that it is more universal than the one which was developed in.

In order to solve global optimization problems James and Li (2015) had anticipated the Social Spider Optimization algorithm (SSO). The framework essentially stands on foraging strategy of social spiders which employs the vibrations spread over the spider web to establish the position of its preys. Compared with other metaheuristics, SSO has greater concert together with evolutionary algorithms and swarm intelligence algorithms. The concert of SSO is stupendous in contrast with the above listed algorithms in all three dissimilar groups of functions including unimodal, multimodaland shifted-rotated multimodal optimization problems.

For decipher optimization tasks Cuevas *et al.* (2013) had anticipated a swarm algorithm called the Social Spider Optimization (SSO). In the anticipated algorithm, individuals emulate a group of spiders which interrelate to each other based on the biological laws of the cooperative colony. The algorithm deems two different search agents (spiders): males and females. Depending on gender, each individual is grouped by a set of dissimilar evolutionary operators which mimic dissimilar cooperative behaviors that are typically found in the colony. The association examines several standard benchmark functions that are normally considered within the literature of evolutionary algorithms.

Mungle *et al.* (2013) suggested that upcoming contracting techniques caused a lot of pressure on the contractors to refurbish the construction quality. In the case of a general contractor, who had the tendency to subcontract a lion's share of the tasks constituting a project and invite a number of bids, the short-listing of a suitable bid which complied with the time, cost and quality of construction project was considered to be a daunting task. Therefore, to address the relative challenge involving contradictory objectives, a Fuzzy Clustering-based Genetic Algorithm (FCGA) approach was introduced. An assessment effort was performed over three test cases involving fluctuating dimensions and intricacies to investigate the efficiency in performance of the novel FCGA vis-a-vis peer techniques.

Moradchelleh (2011) had made a novel proposal regarding the natural and climatic traits of various regions of Iran coupled with modern construction methods and materials making it possible to take decisions to generate relaxed atmosphere for its residents. In accordance with the typological needs, knowledge of historical traditions, contemporary fashions and conservation of the eco-system, construction techniques for the four allotted design-building zones were also green-signaled. Out of the Construction Design Zones (CDZ) decided by taking into account the climatic conditions and the available local construction materials; four CDZs were short-listed. The well-recognized designs and the modern design-construction base were also considered. The investigation thus formed a base for common scientific, methodological, architecturaland planning principles of designing residential and public buildings.

MATERIALS AND METHODS

In the current research, the prefabrication technology is proved to have various benefits related to the construction process. The prefabrication building is tested by prototyping those models which facilitates the forecast of response of the building to the natural disasters especially the earthquakes. The main intention of our work is to predict the Cost Performance (CP) and Time Performance (TP) of the prefabrication process in the construction project. Here, Artificial Neural Network (ANN) is employed with the optimization process in the Enterprise Resource Planning (ERP) approach. In this, various percentages of prefabrication content is added. Further in construction, estimated duration, actual duration, estimated cost and actual cost are used in the ANN process. This network structure is utilized for training with the known data and this process is in the preliminary stage in the prediction process. The input and hidden layer processes the weights α and β used in the ANN structure. By optimizing the weight, different optimization techniques are utilized to appear at the optimal weight of the structure. In our research, Grey Wolf Optimization (GWO), Harmony Search (HS) and Social Spider Optimization (SSO), algorithm is processed and the better algorithm SSO it is utilized to optimize the weight. If the achieved results are not up to the mark, then the training process is repeated again to adapt the structure to the appropriate level necessary to predict the output. Once the attained error values between the output of the experimental values and the predicted values are closely equal to zero then the designed model is utilized. This is further done by predicting the unknown values in the input and for minimizing the time interval of the process (Algorithm 1).

Algorithm 1; Pseudo code for social spider incorporate in time and cost reduction:

```
Step 1: Initialization
Step 2: Fitness computation (Fu)
Step 3: Based on fitness update the new spider population
        {
         Find the number of female and male spiders (X_f and X_m
         Evaluate the weight (Y_u) based on the fitness (F_u)
         Fitness based initialized the population (f^0_{u,v} and m^0_w)
         Find the cooperative operator
                Female cooperative operator (f_u^{w+1})
                Male cooperative operator (m_u^{w+1})
        Mating process find the probability(BT_u)
        Find the fitness for the new spider solution (F_u(new))
        }
Step 5: Store the best spider of the solution so for attained
         Stop until optimal slution (F_optimal) attained
         Iteration = Iteration+1
Step 7: Find the error value (E_u)
```

Prefabrication technology: The prefabricated structure is one of the component member precast, either in factories or in temporary plants set up on the site. These precast members are sent to the site and thereafter they are hoisted and established into a perfect structure. The prefabrication method of construction vis-a-vis the traditional in-situ construction of buildings paves the way for the quicker rehabilitation techniques which adds efficiency and scales down environmental damages. Operationally, the prefabrication represents an innovation in construction which aims to take away as much construction activities as possible from the project site to the factory settings. This assures superior quality and safer production under controlled working conditions.

Benefits of prefabrication: The chief merit of the prefabricated technique is the amazing swiftness of construction process. The quicker urbanization, incredible deficiency of skilled labor and the necessity to have hassle-free construction techniques together triggers the prefab technique to construct houses at a quicker pace.

Another sterling merit of the prefabrication is its quality of resilience. These prefab houses exhibits superior efficiency in execution as they are subjected to stringent checking systems which results in the generation of zero-defect products.

This type of house can be adapted to particular needs/demands/requirements thus making it an ideal place to live in rather than living in traditional slums. The specified requirements may include fire/water/sound proofing. The decreased air and noise pollution at the construction site is an advantage when the site is located adjacent to the densely populated cities.

Performance analysis parameters: The proportion of prefab content for a building was estimated by ascertaining the percentage cost of prefab components out of the total project cost. Hence, the percentage prefab cost represents the percentage of prefab content in a particular building:

$$CP = \left[\frac{EC}{AC}\right] \times \% \tag{1}$$

Where:

CP = The Cost Performance
EC = The Estimated Cost
AC = The Actual Cost

Similarly, the time performance for each building was computed as quotient of initial time estimate and actual completion time:

$$TP = \left[\frac{ED}{AD}\right] \times \% \tag{2}$$

Where:

TP = The Time Performance
ED = The Estimated Cost
AD = The Actual Cost

Artificial neural network: The artificial neural system, an optimized computational technique is entrusted with the task of copying the neural configuration and functioning of the human cerebrum. It is the base for an interrelated framework of deceptively delivered neurons which functions as conduits for data exchange. The data sets are classified by the structure of ascertaining the base sneak past abusing the weights α and β which are modified with the ultimate motive of determining the movement of the input constraints. With an eye on fine-tuning the weights α and β several renovation mechanisms are in Grey Wolf Optimization (GWO), Harmony Search (HS) and Social Spider Optimization (SSO) which are effectively employed to arrive at the ideal weights of the target capacity which is furnished by the contrast between the test and gauge values.

Figure 1 exhibits the vital structural design of the artificial neural system elegantly. It is endowed with the multi-layer neural mechanism (Fig. 1). This is home to three specific layers such as the input, hidden and the output layers. The neural networks are linked to the biological neural networks to perform the functions collectively and separately by the units without an apparent demarcation of subtasks to which diverse units are apportioned. The term "Neural Network" normally represents the models employed in statistics, cognitive psychology and artificial intelligence. In this essential ANN framework, there is a singly shrouded layer along with 1-20 hidden neurons. In the statistical report the ANN equation F_u represents an input layer parameter, O_1 signifies an output layer parameter.

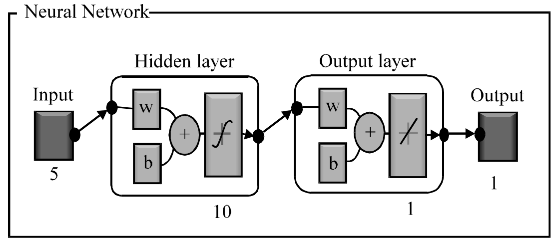

Fig. 1: Natural Network structure

Structure initialization: Initialization process three inputs based the input layer weight α_v and the hidden layer weights β_{uv} are initialized. Input T_U such as prefab percentage, actual duration, estimated duration, actual cost and estimated cost.

Input layer: The input layer contains a number of neurons. All input layer neurons are connected with the hidden layer. It has the four inputs and the input neurons are $u_1, u_2, ..., u_n$. The inputs are $Y_1, Y_2, ..., Y_N$ each neuron possesses the weight which is represented as the uth input layer neuron connected with the vth neuron of the hidden layer like β_{12}, β_{12}, β_{ij}. Input layer basic function equation which is defined as I_1 where I is a basic function of hidden neurons, l is a number of hidden units, β is a weight of the input layer neuron, N is a number of data and Y is a input values. In these value based calculate the basics function:

$$A_f = \sum_{v=1}^{N} Y_u \times \beta_{uv} \tag{3}$$

Where:

A_f = The basics function
β_{uv} = The an input layer weight
u = The number of input

Hidden layer: The hidden layer contains a number of neurons which are named as $h_1, h_2, ..., h_n$ the hidden layers are connected with the output layer by using the neurons. Weight obtaining equation is a_i where I_1 are a number of input layers and the weight α_v and β_{uv} based obtain the activation function.

The ANN is usually based on several optimizations of the weights. In this arithmetical demonstration SSO strategy is observed to achieve the optimal weight.

Social Spider Optimization (SSO): The SSO invariably presumes that the entire search space represents a communal web where all the social-spiders associate with one another. In this novel technique, each and every solution in the search space characterizes a spider location in the communal web. Each spider is given a weight in accordance with the fitness value of the solution. This is signified by the social-spider approach for the SSO process illustrated by the captioned Pseudo code.

Initialization: Initialize the input parameters such as weight α and β which is defined as the is an initial solution of fish and u is a number of solutions and also initialize the parameters such as step, this process is known as initialization process.

$$T_u = \left(Y_{0v}, Y_{1v}, ..., Y_{nv}\right) \tag{4}$$

Where:

T_u = An initial solution, $u \in [1, 2, ..., 10]$ and $v \in [1, 2, ..., 140]$

uth = The value is considered as the number of solution

vth = The value is considered as length of solution:

$$Y_u = \begin{bmatrix} (\text{No.of hidden neuron} \times \text{No.of input data}) + \\ \text{No.of hidden neuron} \end{bmatrix} \tag{5}$$

Where:

Total input = 5

Hidden neuron (h) = 20

Based on Eq. 2, the attained solution length is 140 and the solution range lies between $-10 \leq T_{uv} \leq 1$. According to the initial solution based output as performance of cost and duration.

Fitness function: Evaluate the fitness value of each arbitrarily generated particle assess the optimization fitness functions:

$$F_u = \sum_{v=1}^{h} \alpha_v \times \left[\frac{1}{1 + \exp(-\sum_{u=1}^{N} Y_u \beta_{uv})} \right] \tag{6}$$

Where:

Fu = A fitness function α and β are weights

Y = The input parametera

u = The number of inputs

v = The number of weights

h = The number of hidden neurons this equation based fined the fitness value of the process

New population updation by using following procedure: The novel technique envisages two diverse search agents (spiders) such as the male and female. In accordance with the gender, each and every individual is undergoes a set of diverse evolutionary operators which imitates the various cooperative trends which are habitually presumed inside the colony. Taking X as the total number of n-dimensional colony members, the number of male X_m and females X_f spiders in the total population X is defined:

$$\begin{aligned} X_f &= \text{floor}\left[0.9\text{-rand}.025).X\right] \text{and} \\ X_m &= X\text{-}X_f \end{aligned} \tag{7}$$

Where:

rand = The random number between [0, 1]

floor (.) = The maps; a real number to an integer number

Weight assignation: In the biological metaphor, the spider size represents the unique feature which estimates the individual skills to efficiently carry out its delegated functions. Each and every individual (spider) is allocated a weight Y_u which characterizes the solution quality which is related to the spider u (regardless of the gender) of the population T. The weight of each and every spider of T is evaluated by means of Eq. 8:

$$Y_u = \frac{F(T_u)\text{-worst}_T}{\text{best}_T\ \text{-worst}_T} \tag{8}$$

where, $F(T_u)$; is the fitness value obtained by the evaluation of the spider position T_u with regard to the objective Function F. The values worst_T and best_T are calculated Eq. 9:

$$\begin{aligned} \text{best}_T &= \frac{\min}{w = \{1, 2, ..., N\}} (F(T_k))\text{and} \\ \text{worst}_T &= \frac{\max}{w = \{1, 2, ..., N\}} (F(T_k)) \end{aligned} \tag{9}$$

Fitness based initializes the population: The algorithm begins by initializing the Set S of X spider positions each spider position f_u and m_u is an dimensional vector containing the parameter values to be optimized. Such values are randomly and uniformly distributed between the pre specified lower initial parameter bound B_v^{low} and the upper initial parameter bound B_v^{high} just as it distributed by using Eq. 8 and 9:

$$\begin{aligned} & f_{u,v}^0 = B_v^{low} + \text{rand}(0,1) \times (B_v^{high} - B_{jv}^{low}) \\ & (u = 1, 2, ..., V_m,\ v = 1, 2, ..., n) \end{aligned} \tag{10}$$

$$m^0_{w,v} = B^{low}_v + rand(0,1)\times(B^{high}_v - B^{low}_{jv}) \quad (w = 1, 2, ..., V_m,\ v = 1, 2, ..., n) \tag{11}$$

Where:
u, v and w = The parameter and individual indexes, respectively
0 = The initial population
$f_{u,v}$ = The vth parameter of the uth female spider position

Cooperative operators

Female cooperative operator: The female spiders bring in either charm or disgust over others irrespective of the sexual orientation. In the case of a specified female spider, the corresponding charm or disgust is habitually generated over the other spiders which are evident by their vibrations which are released over the communal web. As these vibrations invariably rely depend on the weight and distance of the members which have instigated them, sturdy tremors are generated by the giant spiders or the neighboring members which are situated near the person observing them. The former case is concerned with the transformation with respect to the closest member to u which possesses a greater weight and generates the vibration $Vibc_u$. The latter case involves the modification with regard to the best individual of the whole population T which generates produces the vibration $Vibb_u$. The female vibration $Vibc_u$ and $Vibb_u$ are estimated by means of Eq.8:

$$Vibc_u = w_c\times e^{-d^2_{u,c}}\ Vibb_u = w_b\times e^{-d^2_{u,b}} \tag{12}$$

The vibration $Vibc_u$ are perceived by the individual $u(T_u)$ as a result of the information transmitted by the member $c(T_c)$ who is an individual that has two important characteristics: it is the nearest member to i and possesses a higher weight in comparison to $u(w_c > w_u)$. The vibration $Vibb_u$ are perceived by the individual u as a result of the information transmitted by the member $b(T_b)$ with b being the individual holding the best weight that ids fitness of the entire population T such that $w_b = \max_{w\in(1, 2, ..., N)} w\ (w)$.

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:

$$f^{w+1}_u = \begin{cases} f^w_u + \alpha\times Vibc_u\times(T_c - f^w_u) + \beta\times Vibb_u\times\left(T_b - f^w_u\right) + \delta \\ (rand - \frac{1}{2}) \text{ with probability PF} \\ f^w_u - \alpha\times Vibc_u\times(T_c - f^w_u) + \beta\times Vibb_u\times\left(T_b - f^w_u\right) + \delta \\ (rand - \frac{1}{2}) \text{ with probability 1-PF} \end{cases} \tag{13}$$

Where:
α, β, δ and rand = Random numbers between [0, 1]
w = The iteration number
T_c and T_b = The nearest member to u that holds a higher weight and the best individual of the entire population T

Male cooperative operator: Male members possessing a weight value greater the median value within the male population is deemed as the dominant individuals D. Conversely, those within the median value are considered as the non-dominant ND males. With the intention of performing the corresponding evaluation, the male population $M(M = \{m_1, m_2, ..., m_{nm}\})$ is orchestrated in accordance with their weight value in the descending order. Hence, the individual having weight $w_{V_{f+m}}$ situated in the middle is taken as the median male member and the vibration of the male $Vibf_u$ evaluated with the help of Eq. 10. The vibration $Vibf_u$ observed by the individual $u(T_u)$ on account of the data communicated by the member $f(T_f)$ with f being the closest female individual to u:

$$Vibf_u = w_f\times e^{-d^2_{u,f}} \tag{14}$$

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

$$m^{w+1}_u = \begin{cases} m^w_u + \alpha\times Vibf_u\times(T_f - m^w_u) + \delta\times(rand - \frac{1}{2}) \text{ if } w_{V_{f+i}} > w_{V_{f+m}} \\ m^w_u + \alpha\times\left(\dfrac{\sum_{h=1}^{V_m} m^w_h \times w_{V_{f+h}}}{\sum_{h=1}^{V_m} w_{V_{f+h}}} - m^w_u\right) \text{if } w_{V_{f+i}} \le w_{V_{f+m}} \end{cases} \tag{15}$$

Where:
T_f = The nearest female individual to the male member u
$\left(\dfrac{\sum_{h=1}^{V_m} m^w_h \times w_{V_{f+h}}}{\sum_{h=1}^{V_m} w_{V_{f+h}}}\right)$ = The weighted mean of the male population M

By employing the above-mentioned operator, two diverse phenomena are generated. In the former, the set D of particles is fascinating to others because it is done with the intention of inciting the act of mating. This effects the permission of the integration of diversity into the population. In the latter, the set ND of particles is fascinated to the weighted mean of the male population M and this phenomenon is effectively employed to regulate the search procedure in accordance with the average performance of a subgroup of the population.

Mating process: The mating in a social-spider colony is carried out by the leading males and the female members. In such a scenario, when a leading male m_g spider ($g \in D$) finds a set E^g of female members within a specified range r(which is considered as the range of mating), it mates, producing a new brood T_{new} which is produced taking due account of the entire elements of the set R^g which, in turn, has been created by the union $E^g \cup m_g$. It is pertinent to note that if the set E^g is vacant, the mating function has to be abandoned. The range r is concisely described as the radius which is dependent on the dimension of the search space. Now, the female $(F = \{f_1, f_2, ..., f_{v_f}\})$ and male $(M = \{m_1, m_2, ..., m_{v_m}\})$ are randomly initialized where $T = \{T_1 = f_1\ T_2 = f_2, ..., T_{v_f} = f_{v_f}, T_{v_{f+1}} = m_1, T_{v_{f+2}} = m_2, ..., T_v = m_{v_m}\}$ and the radius mating is calculated:

$$r = \frac{\sum_{v=1}^{n} (B_v^{high} - B_v^{low})}{2 \times n} \tag{16}$$

In the mating process, the weight of each involved spider (elements of R^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 B_{T_U} of each member is assigned by the roulette methodwhich is defined as follows:

$$B_{Tu} = \frac{w_u}{\sum_{v \in R^w} w_v} \quad \text{where } u \in R^g \tag{17}$$

When the new spider is generated, it is contrasted with the new spider candidate T_{new} having the worst spider T_{wo} of the colony, depending on their weight values. If the new spider is superior to the worst spider, the worst spider is substituted by the new one. If not, the new spider is eliminated and the population does not undergo any modifications. On the contrary, in the case of substitution, the new spider takes control of the gender and index from the substituted spider, thus ensuring that the whole population R preserves the original rate between female and male members. In accordance with this procedure, the optimum hidden layer and neuron of the neural network procedure are evaluated.

Optimal solution: Based on the above mentioned process, we attain 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 values based predict the output which is performance of cost and performance of duration:

$$F_{u(optimal)} = \sum_{v=1}^{h} \alpha_{v(optimal)} \times \left(\frac{1}{1+\exp(-\sum_{u=1}^{N} Y_u \beta_{uv(optimal)})} \right) \tag{18}$$

Output layer: The output layer has a number of neurons. The hidden layer neurons are connected with the output layer by the neurons. Each connection has a weighted value such as a_1, a_2, ..., a_n. The basis function of the Output units is expressed by the Eq. 18 is O_l:

$$O_l = \sum_{u=1}^{n} \alpha_u\ \sigma(F_{u(optimal)}) \tag{19}$$
$$l = 1 \text{ and } 4 \in [1, ..., n]$$

Where:

α = The weights range from -50 to 50
I = The input parameters
u = The number of inputs

The error value calculation the equation which is defined as E_u. v is the number of weights and h is the number of hidden neurons:

$$E_u = \sqrt{\frac{\sum_{u=1}^{ND} (D_u - P_u)^2}{ND}} \tag{20}$$

Where:

ND = The number of the data
D = The desired value
P = The predicted value
u = 1, 2, ..., n

By using this Eq. 20, the error value is getting from the difference between desired value and predicted value. The proposed research results are achieved in the working platform of the MATLAB 2014 with the system configuration i5 processors with 4GB RAM which is used in the ANN process.

RESULTS AND DISCUSSION

By utilizing the ANN construction process parameters such as the cost performance and time performance are obtained in the prefabrication technology. The optimized optimal artificial intelligence network with SSO algorithm optimized elegantly performs the absorbing function of finding the optimal solutions of α and β. Subsequently, the optimal solutions of the weight with input constraints are arrived at with the assistance of the amazing SSO process. The major objective of the ANN is to forecast the output like realtime experiment to minimize the error. In other words, the differential error between realtime output and the attained output from ANN is found to be near equal to zero. With the result, the related output is evaluated by utilizing the performance measures.

Convergence graph: The graphs showing below successfully show the performance analysis parameters fitness graphs based on iteration of the GWO, SSO and HS 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 symbolized in the X-axis and fitness in the Y-axis.

Figure 2 shows the convergence graph for the prefabrication technology performance parameters for the construction together with the fitness values. The graph fundamentally tackles the SSO process offering the minimum fitness in maximum iteration. It is visible from the graph, that the minimum of the wind power generation is realized in SSO technique which is 0.1 in 100th iteration. Behaving of the convergence graph initial iteration fitness value will be high based on the objective function of the algorithm then minimizes the error values. The SSO is performed better when comparing with GWO and HS in this error graph. The graph effective furnishes the perfect fitness values illustrating the amazing outcomes of the social spider optimization technique.

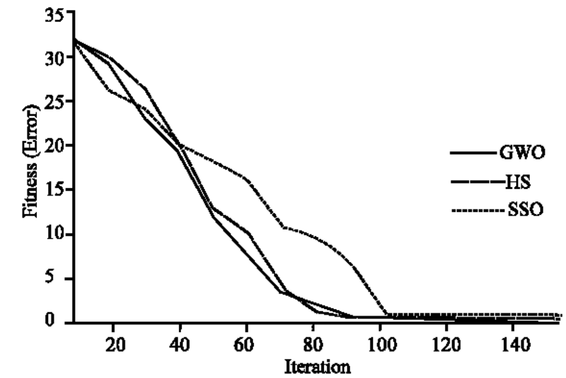

Fig. 2: Convergence graph

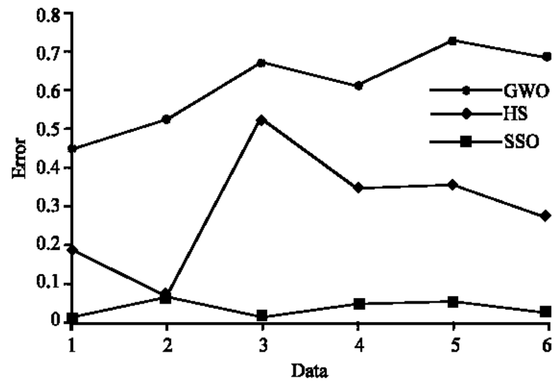

Fig. 3: Time performance in prefabrication construction

Error values of output parameters in different algorithm: In this study, testing data varied and the error value is calculated for the certain input parameters to predict the cost and time performance of the prefabrication technology the results are shown in Fig. 3.

Figure 3 shows that the time performance of the prefabrication technology process. In this, the time performance of the different data error values of different algorithm. The minimum error value of the proposed method in initial data compared to GWO the difference is 19.12 and HS is 2.68. The graph shows SSO is 0.414 the minimization of error value is predicted when compared with GWO and HS. The error value calculated by use the experimental results and predicted value of the ANN process.

Figure 4 shows that the cost performance of the prefabrication technology process. The cost performance of the optimization techniques the minimum error value of the cost performance is 0.643 in SSO process and the testing input data based changing the predicted values. The error value of GWO is 5.388 and HS is 30.31.

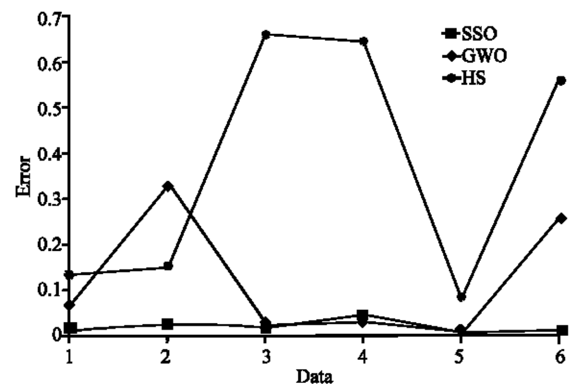

Fig. 4: Cost performance in prefabrication construction

Experimental results and predicted values for proposed method: In Neural Network process, the testing results and original values for the wind power generation the thermodynamic parameter are shown in Table 1. ANN with optimization technique the nearby values occur in SSO technique.

Table 1 Shows that the actual values and predicted results of proposed method in prefabrication technology.

Table 1: Estimated results for testing data

Inputs					Outputs (performance)			
					Actual values		Predicted values (SSO process)	
Prefab content (%)	Actual duration	Estimated duration	Actual cost	Estimated cost	Duration	Cost	Duration	Cost
30	48	24	7,50,000	3,15,000	0.5	0.42	0.499	0.419
38	52	28	6,75,000	3,03,750	0.54	0.45	0.546	0.447
59	38	28	16,85,775	12,13,758	0.75	0.72	0.766	0.727
67	42	36	18,50,565	14,43,441	0.86	0.78	0.854	0.821
72	42	40	29,50,775	28,91,760	0.95	0.98	0.944	0.980
88	19	24	9,50,000	11,21,000	1.26	1.18	1.260	1.179

First data consider the prefab content in 30% and the time duration, cost will be consider the performance results for original is 0.5 in duration and 0.42 in cost the predicted values are 0.499 and 0.419 in SSO method. In the same process for prefab content as 38, 59, 67, 72 and 88% the SSO value is shown in Table 2. All the testing data has the nearby duration and cost performance value attained in the SSO process.

CONCLUSION

In prefabrication technology performance, time and cost parameters of the construction process is predicted by using the ANN with the SSO algorithm which attains amazing, accurate ideal values of the weights in the model. Based on the weights universal optimum solution which illustrates the adaptability to choose the design variables are conducted for the multivariable optimization problems. During this process the different prefab content; cost and duration the convincing output results are considered and observed which is nearly equal to the data set minimum error value achieved in the optimization method. With their excellent optimization techniques for the performance parameters of the prefabrication construction process ANN will look towards further unbelievable improvement methodologies for the achievement of diminished errors in future, ANN will look towards further unbelievable improvement methodologies for the achievement of diminished errors with their excellent optimization techniques for the performance parameters of the prefabrication construction process.

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