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Cost Monitoring and Management Algorithms in the Construction Process of Building Projects



Abstract: - Construction project cost estimation is an essential activity in construction-based fields; it offers a valuable source for the project feasibility studies and the design plan comparisons, and the accuracy can directly influence project investment decisions. A successful implementation of project cost forecasts makes it easier to control and manage project costs. Therefore, this paper presents the Ladybug Reptile Search Algorithm_ Deep Maxout Network (LRSA_DMN) (LRSA_DMN) to estimate construction costs. Additionally, LRSA is included to correct DMN weights. Furthermore, Bootstrap scheme is used to augment data and use this data to input the DMN for cost estimation. In addition, features are selected using a Weighted Correlation Coefficient to choose the best features for further processing. The test results show that LRSA_DMN performs better regarding MSE, RMSE, and Accuracy by 0.092, 0.371, and 0.907, respectively.

Keywords: Construction Management, Building projects, Cost estimation, Reptile Search Algorithm, Deep Maxout Network.

1. Introduction

Construction project management mainly includes initial investment estimate, program, expansion [11][12], stage project budgeting, project completion, etc. Construction project management focusses on determining construction cost investments [13]. The effectiveness of project depends on the construction savings cost [10]. Building and construction costs, or construction costs, play the vital role in estimating investment value of construction project. Therefore, cost estimation is very crucial for building projects [6]. Cost forecasting is necessary for every company because it sets costs and allocates resources in the project life cycle [9].

Cost prediction/estimation is one of the leading topics of information for determining the start of construction [8]. Cost estimation is an essential topic in construction projects. The lack of a construction project leads to low and high costs. The use of multiple methods throughout the project life cycle should provide project sponsors with cost-related information and support complex decision-making processes [14]. Moreover, Cost estimation is essential in pre-construction price accounting and easy preparation for any construction project. There is a lot of uncertainty about price estimates at the beginning of a construction project. Therefore, an urgent need is to prepare an action plan to reduce the price uncertainty and long forecasts [5].

Many cost estimation methods are applied for building price estimation, like case-based reasoning, statistical regression, artificial neural networks (ANN), and Support Vector Machine [15]. The growth of these modeling schemes is often using historical information and construction experience from previous projects, as well as the prior knowledge of the modeler [16][3]. The Back Propagation Neural Network (BPNN) [26] is the mathematical scheme compared to the other learning methods, nevertheless it provides great application value in the project cost estimation. Though, traditional BPNN estimation models consume weaknesses, such as low statistical accuracy, poor stability, and low generalizability [6].

2. Literature survey

T. Q. D. Pham *et al.* [1] present a rapid Machine Learning (ML) and the optimization that permits for the quick estimation of construction expenses, enhancing construction companies' operational efficiency and competitiveness. It involves data processing, a machine learning regression method, and model evaluation. The optimization issue below restrictions has been resolved, allowing customers to identify the ideal building costs based on their choices. Still, Optimization processes and interrelated features are more difficult to combine.

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Xiaojing Ding and Qiulan Lu [2] introduced a model for building cost estimation and a NN prediction to increase a prediction model's accuracy and the application technology. By utilizing Building Information Modelling (BIM) technology to effectively leverage their engineering cost benefit and apply these benefits in the building industry and the cost management, organizations can reap significant advantages and boost enterprise development, but fail to focus on quantitative calculations.

VB Chandanshive and A.R. Kambekar [3] developed multi-layer NN trained with regression method for construction cost forecasting (INR). Early blocking methods and Bayesian regularization methods are used to improve the neural network's generalization ability and avoid redundancy. The trained neural network successfully predicted the initial construction costs and also showed an increase in forecast accuracy and data volume. However, optimization algorithms were not included to make prediction better.

Mohammed H. Ali and Abbas M. Abd [4] used ANN and the Particle Swarm Optimization approach (ANN-PSO) to anticipate a price and delay of the construction projects and demonstrate hazards involved. Risk factors were recognized and analyzed by Probability and the Impact Analysis that served as the model inputs. The ANN was developed in conjunction with BP optimization approach to evaluate the ANN-PSO model's performance. The ANN-BP shows better performance. However, better features should be introduced to reduce errors.

Takzad Khalaf *et al.* [5] introduced PSO to compute construction price and duration of the construction projects. The PSO model helps engineers to make the decisions in early stages of design phase. Using this method, accurate decisions can be obtained even if the information is not early. The PSO method is suitable for addressing project management issues and provides better tool for finding best solutions with different parameters. However, a process needs to consider other models to compute a cost and duration of green buildings.

T.Q.D. Pham *et al.* [6] developed a BPNN guided by PSO, which can more accurately predict construction project costs and deliver a framework for the cost management throughout a project life cycle. This method has a faster conversion rate, more generalizability, and more accurate prediction, but Long Short-Term Memory (LSTM) was not considered to predict cost.

Duc Hoc Tran [7] developed a novel multiple-objective social group optimization (MOGSO) to solve time with cost trade-off issue in the generalized construction projects was introduced. MOSGO changes the working method of the original algorithm and turns it into a non-zero algorithm, which improves the balance between the exploration and the use of the optimization algorithm. The non-dominated global optimal solutions are selected using empirical methods to help decision makers reach a compromise solution. This method solves the general relationship in the theoretical formulation of the TCT problem. However, does not implement multi-purpose environments in various fields.

Nabil Ibrahim El-Sawalhi and Omar Shehatto [8] developed an ANN for estimating the initial cost of Gaza defense development project. This method helps all parties involved in a construction project (contractor, owner, etc.) to get the total price. The ANN was successful in estimating the costs of the construction project without needing more detailed images. The extracted model did not include new variables to gain better prediction results.

The goal is to provide an in-depth visualization model for construction cost estimation using LRSA_DMN. Pre-processing is used to remove unnecessary construction project data. Apart from that, the Bootstrap method is also used to expand the data. Data augmentation helps prevent redundancy when you train Deep Learning (DL) models. In addition, a Weighted Correlation coefficient is employed to choose best features, thus making process more accurate. It also increases the methods predictive power by choosing the most critical variables and discarding redundant and irrelevant variables.

This research's primary contributions are:

A new LRSA_DMN is created to estimate construction costs. In addition, LRSA integrates RSA and LBO, using the best features of both methods. RSA encourages crocodile hunting activities. There are two main actions to achieve crocodile behavior: namely encircling the road by high road or stealth road, and hunting by working together to catch or by working together. LBO is also inspired by the natural habit of earthworms looking for a warm location to live in the winter.

The structure of the research paper is as follows: The section 2 presents the literature survey on several construction cost estimations; Section 3 explains the projects construction cost structure; Section 4 delivers the brief explanation of LRSA_DMN; Section 5 presents projects results and details; Section 6 concludes the paper.

The following issues are noticed in the relevant work:

Construction project management is becoming increasingly challenging due to increasing complexity and uncertainty. The limitations of traditional time and cost monitoring methods lead to increased time and cost that significantly impede project completion. The time and cost implications of every phase of the construction projects are critical to successful completion and management of the project. Delivery and estimating in the construction industry present many challenges, including the availability of historical data, project complexity, time constraints, cost variability, technical integration small and a competitive delivery environment.

3. Structure of building project costs

Project cost refers to a construction projects expected or actual spending during its construction term. In the today's market, the project cost can mean two distinct things based on demand and supply factors. Analysis of entire investment costs of project's fixed assets or fixed expenses from the point of view of the entrepreneur (owner). Investors need to complete various tasks, such as investment decisions, research and design, bidding, construction, and approval of the completion to get the expected results from the investment project. From this point of view, project cost is total investment in a building project, as depicted in the Figure 1.

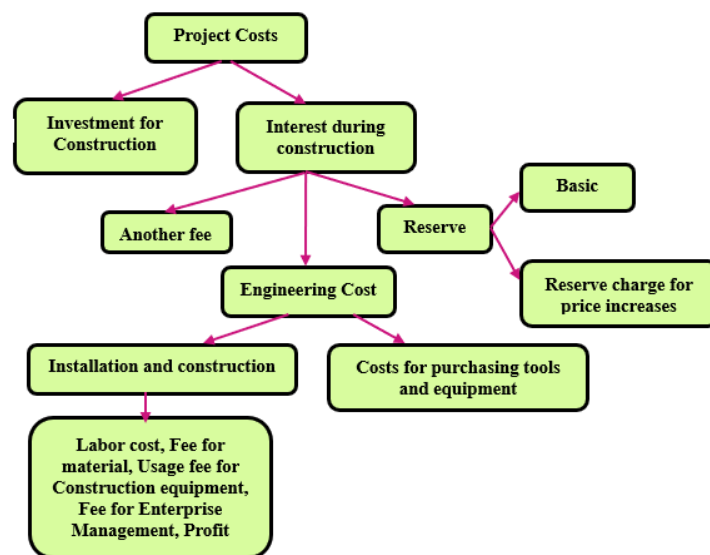


Figure 1. Building project cost structure

4. Proposed Methodology

This section describes LRSA_DMN for construction cost estimation. The steps involved in the construction cost estimation of a building project are pre-processing, feature selection, data augmentation, and construction cost estimation. The pre-processing step first uses min-max normalization to remove irrelevant data, and then the Weighted correlation coefficient selects the best features for further processing. Features are selected, and data is augmented using Bootstrap. Once the data is augmented, the DMN estimates construction costs. The LRSA trained the DMN, where, LRSA integrates RSA and LBO to estimate construction costs.

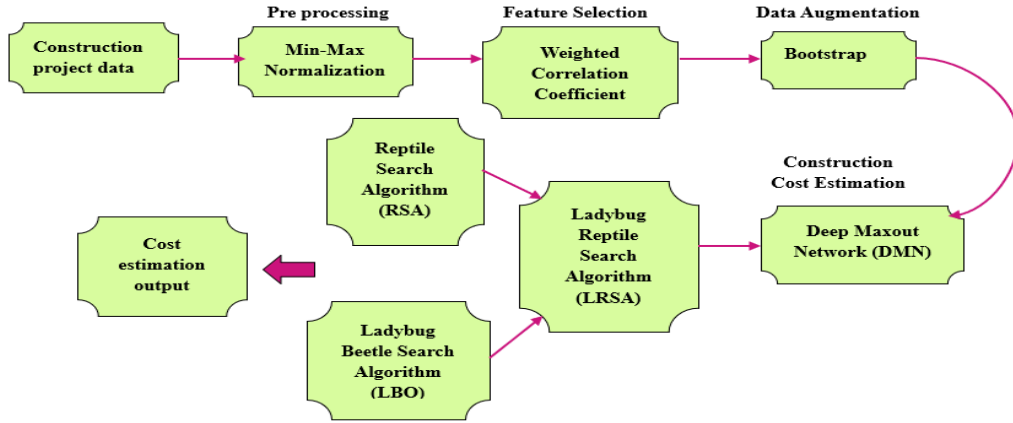


Figure 2. Structural diagram of LRSA_DMN for cost estimation

4.1. Data acquisition

Assume a construction project dataset H that contains the g amounts of data,

$$H = \{P_1, P_2, \dots, P_l, \dots, P_g\} \tag{1}$$

where, g is total data, and P_l is l^{th} data. The input P_l of dimension $a \times b$ is passed to the preprocessing phase.

4.2 Pre-processing

A data collected from dataset P_l undergoes a preprocessing where input data is preprocessed by min-max normalization [5]. The data is converted into transformed format to make data easier to understand. The method applies the linear transformation to input data. Within range, $new_max(e) - new_min(e)$, min-max normalization converts the value c to c' . The min-max normalization formula is given below.

$$c' = \frac{[c - \min(e)] * [new_max(e) - new_min(e)]}{[\max(e) - \min(e)]} + new_min(e) \tag{2}$$

where, $\min(e)$, and $\max(e)$ is minimal and maximal attribute's value. The Min-Max normalized output is denoted as c' of dimension $a \times b$.

4.3 Feature selection

A processed data is employed to choose essential features from input data to limit number of features using the weighted correlation coefficient [19]. Here, the pre-processed dimension data $a \times b$ is reduced to a dimension of $a \times d$, where $b > d$. For each data set, the feature with maximum value is considered finest feature. A correlation coefficient is expressed as a relationship between two sets of information, as shown by the following formula:

$$k_y = \frac{\sum y_z (J_z - \bar{J}_y)(R_z - \bar{R}_y)}{\sqrt{\sum y_z (J_z - \bar{J}_y)^2} \sqrt{\sum y_z (R_z - \bar{R}_y)^2}} \tag{3}$$

where, J_z is the candidate feature, R_z is the target, $\bar{J}_y = \sum y_z J_z$, $\bar{R}_y = \sum y_z R_z$ and y_z are the weights. Therefore, the selected features are represented as I of dimensions $a \times d$. After calculating the weighted

correlation coefficient for each feature, the top k feature with maximal score is chosen as best feature and is forwarded to data augmentation.

3.4 Data Augmentation

This is a process of enhancing data by creating novel data alike to raw data. This process reduces redundancy problems and promotes system scalability. The selected feature I is given to the Bootstrap method [20], a descriptive method used to determine statistics, like the mean or standard deviation, by replacing the use of the data sample, taking a small sample with several repetitions, determining the statistics, and then considering meaning of these statistics. The augmented data is written by L of size $P \times d$, where $a > P$.

3.3. Construction cost estimation by LRSA_DMN

Construction cost estimation is performed using the LRSA_DMN. Here, DMN is constructed by integrating LRSA with DMN [21] to select the best weights available in DMN. DMN can solve different optimization problems by processing data in real time. It can handle large data, and is easier to process. The DMN model and training procedure are described below.

-DMN structure

The DMN [19] is an ordered Maxout that employes various activation functions. DMN is fast converging, more generalizable, and easy to optimize with other networks. Learning to use new features is more accessible, improve performance and makes it easier to divide the parts. Maxout networks help improve accuracy and provide reduced optimization, called fast models. Maxout units, on the other hand, represent training activations. The input given to the DMN is the specified component, denoted by L . The DMN is a trained activation mechanism that takes a multi-layered model. Consider an input L , which is the primary input vector of hidden layer, and activation of the hidden units is expressed by,

$$k_{t,u}^1 = \max_{u \in [1, d_1]} h^U \omega_{tu} + f_{tu} \tag{4}$$

$$k_{2,u}^2 = \max_{u \in [1, d_2]} k_{j,u}^{1^U} \omega_{tu} + f_{tu} \tag{5}$$

$$k_{j,u}^v = \max_{u \in [1, d_k]} k_{t,u}^{v-1^U} \omega_{tu} + f_{tu} \tag{6}$$

$$k_{j,u}^n = \max_{u \in [1, d_p]} k_{j,u}^{n-1^U} \omega_{tu} + f_{tu} \tag{7}$$

$$k_j = \max_{u \in [1, d_p]} k_{j,u}^n \tag{8}$$

where, n is total DMN layers, $\omega_{t,u}$ and f is weights and bias. The output produced by DMN is a cost-estimated result denoted by Q . Figure 2 shows the DMN model.

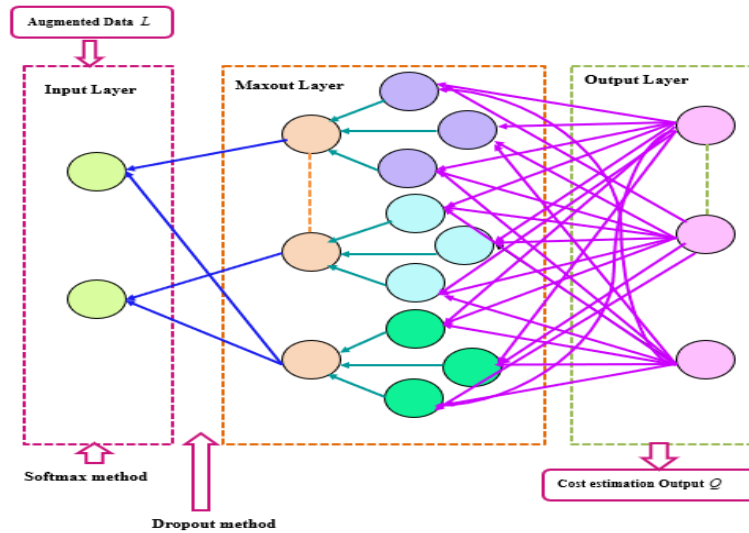


Figure 2. DMN structure

- Training of LRSA

This section discusses the DMN training method, which employs the LRSA algorithm. The LRSA trains classifier weights to obtain the ideal solution. RSA [17] is an optimization technique modeled around Crocodile encircling and hunting behaviors. Here, the advantage of the RSA is that the model is very elastic. LBO [22] is an optimization algorithm inspired by ladybugs behavior as they search for warm places in the winter. LBO's innovation is reflected in the optimization speed, and the search speed during processing is still vital. Therefore, the mixture of LBO and RSA to form LRSA provides a better solution to large-scale and short-term problems. The algorithm flow of the entire LRSA training process is explained below.

-Initialization

Candidate solutions are randomly initialized in the first step and are expressed as,

$$S = \begin{bmatrix} S_{1,1} & \dots & S_{1,s} & S_{1,c-1} & S_{1,c} \\ S_{2,1} & \dots & S_{2,s} & \dots & S_{2,c} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ S_{m-1,1} & \dots & S_{m-1,r} & \dots & S_{m-1,c} \\ S_{m,1} & \dots & S_{m,r} & S_{m,c-1} & S_{m,c} \end{bmatrix} \quad (9)$$

where, $S_{m,c}$ is dimension c of crocodile m , S is randomly generated candidate solution, and the preliminary equation changes,

$$S_{t,r} = \alpha \times (s_a - q_a) + q_a \quad (10)$$

where, α is random number, s_a and q_a is upper and the lower bounds of optimization issues.

-Fitness function

Fitness functions are employed to compute ideal solution of optimization issue. Here, ideal solution is determined based on the smallest MSE value, which is defined as:

$$Fit_{\min} = \frac{1}{b} \sum_{i=1}^b (M_i^* - Q)^2 \quad (11)$$

where, b , M_i^* , and Q is population size, expected result, and predicted result of DMN.

-Encircling

This section elucidates basic features of the RSA. When under attack, the crocodile has two movements, namely walking on its stomach and walking high. Based on these two actions, the crocodile finds the best place to find the food after many trials. In addition, the surrounding phase finishes the initial half of whole cycle. So, an Alligator Band formula for the repositioning is:

$$S_{t,r}(w+1) = \begin{cases} A_r(w) \times (-\omega_{t,r})(w) \times \delta - G_{t,r}(w) * \alpha, & w < \frac{X}{4} \\ A_r(w) \times p_{(x_1,r)} \times EF(w) \times \alpha & w \leq 2\frac{X}{2} \text{ and } w > \frac{X}{4} \end{cases} \quad (12)$$

where, $A_r(w)$ is ideal crocodile at iteration w , $S_{t,r}(w+1)$ is t^{th} solution position in direction r at the iteration $w+1$, and $S_t(w)$ is ideal solution in t^{th} direction during the iteration w , and $G_{t,r}(w)$ represents the deviation between positions t^{th} of the solution in r^{th} dimension during the iteration w . The difference between iterations is that α be random number among 0 and 1, s_1 and s_2 are random number of -1 and 1, δ is parameter for sensitivity. Now, R is highest iterations. In addition to that, the calculation model for the hunting operator $\omega_{t,r}(w)$ is as follows:

$$\omega_{t,r}(w) = A_r(w) \times U_{t,r} \quad (13)$$

The minimization function $G_{t,r}(w)$ is used to reduce the search space, and the calculation formula is:

$$G_{t,r}(w) = \frac{A_t(w) - p_{(x_2,r)}}{A_t(w) + o} \quad (14)$$

where, o is random numbers, $EF(w)$ represents the importance of evolution, and the numerical formula is:

$$EF(w) = 2 \times x_3 \times \left(1 - \frac{1}{X}\right) \quad (15)$$

where, x_3 is random number, $U_{t,r}$ is percentage difference among the position r of ideal solution and r^{th} position of current solution.

$$U_{t,r} = \beta + \frac{S_{t,r} - K(S_t)}{A_r(w) \times ((s_a)_r - (q_a)_r) + o} \quad (16)$$

where, $K(S_t)$ is average location of solution t , and calculation formula is:

$$K(S_t) = \frac{1}{\ell} \sum_{r=1}^{\ell} S_{t,r} \quad (17)$$

-Hunting phase

This section describes the working part of RSA. In this phase, crocodiles follow two hunting strategies, cooperative and coordinated hunting. In contrast to the surrounding strategy, the crocodile strategy allows him to

get closer to the targets because of his strength. Therefore, the development phase will find a solution that is close to the optimal value after many trials. In addition, the methods developed in this optimization section aim to carry out an efficient search close to ideal solution and emphasize the communication between these solutions. The exploitation search is done on $w \leq 3 \frac{X}{4}$ and $w > 2 \frac{X}{4}$, but hunting is carried out on $w \leq U$ and $w > 3 \frac{X}{4}$.

Additionally, the location has been updated as,

$$S_{t,r}(w+1) = \begin{cases} A_r(w) \times G_{t,r}(w) * \alpha, & w \leq 3 \frac{X}{4} \text{ and } w > 2 \frac{X}{4} \\ A_r(w) - \omega_{t,r}(w) \times \delta - G_{t,r}(w) * \alpha & w \leq U \text{ and } w > 3 \frac{X}{4} \end{cases} \quad (18)$$

Here, the main techniques for the regeneration of the crocodile were chosen, given by:

$$S_{t,r}(w+1) = A_r(w) \times G_{t,r}(w) * \alpha; \quad w \leq 3 \frac{X}{4} \text{ and } w > 2 \frac{X}{4} \quad (19)$$

To improve the performance of RSA, the concept of LBO was introduced in RSA. Therefore, the update position of the ladybug can be expressed as follows:

$$C_a(\kappa+1) = C_a(\kappa) + rand \times (C_o(\kappa) - C_a(\kappa)) + rand \times (C_o(\kappa) - C_{o-1}(\kappa)) + rand \times |Y_a|^{\frac{\kappa}{D(\kappa)}} \times C_a(\kappa) \quad (20)$$

$$C_a(\kappa+1) = C_a(\kappa)(1 - rand + rand|Y_a|^{\frac{\kappa}{D(\kappa)}}) + 2randC_o(\kappa) - rand \times C_{o-1}(\kappa) \quad (21)$$

where, $D(\kappa)$ is distance among 0 and 1, partitioned into unequal parts $D(\kappa)$, $rand$ is the random number= (0,1), $C_a(\kappa+1)$ is a^{th} individual location at $\kappa+1^{th}$ iteration, $C_a(\kappa)$ is the location of a^{th} individual at κ^{th} iteration.

Consider,

$$C_a(\kappa+1) = S_{t,r}(w+1), C_a(\kappa) = A_r(w), C_o(\kappa) = G_o(\gamma), \text{ and } C_{o-1}(\kappa) = G_{o-1}(\gamma)$$

$$S_{t,r}(w+1) = A_r(w)(1 - rand + rand|Y_a|^{\frac{\kappa}{D(\kappa)}}) + 2randG_o(\gamma) - rand \times G_{o-1}(\gamma) \quad (22)$$

$$A_r(w) = \frac{1}{(1 - rand + rand|Y_a|^{\frac{\kappa}{D(\kappa)}})} [S_{t,r}(w+1) - 2randG_o(\gamma) + rand \times G_{o-1}(\gamma)] \quad (23)$$

Substitute equation (23) in (19),

$$S_{t,r}(w+1) = \frac{1}{(1 - rand + rand|Y_a|^{\frac{\kappa}{D(\kappa)}})} [S_{t,r}(w+1) - 2randG_o(\gamma) + rand \times G_{o-1}(\gamma)] \times G_{t,r}(w) * \alpha; \quad w \leq 3 \frac{X}{4} \text{ and } w > 2 \frac{X}{4} \quad (24)$$

where, Y_a is the ratio of the solution cost to total cost of each solution in an iteration κ .

where,

$$Y_a = \frac{g(C_a(\kappa))}{\sum_{\gamma=1}^{D^\kappa} g(C_\gamma(\kappa))} \tag{25}$$

Thus, the 24th equation is the final LRSA_DMN that estimates the building cost very effectively.

-Feasibility evaluation

The fitness function is computed for each iteration once the Reptiles' positions have been updated. If the computed solution outperforms the current solution, the new solution is designated as the optimal solution.

-Termination

Repeat all the steps above until you determine the best solution. Algorithm 1 shows pseudocode of LRSA.

Algorithm 1. LRSA pseudocode

| |
|--|
| Input: S |
| Output: $S_{t,r}(w+1)$ |
| Start the crocodile population |
| while ($w < X$) do |
| Compute fitness of candidate solution |
| Evaluate perfect solution |
| Renew the EF by 15th equation |
| for ($t = 1$ to m) do |
| for ($t = 1$ to ℓ) do |
| Renew ω, G, U by 13, 14, and 16 th equation |
| if ($w < \frac{X}{4}$) then |
| $S_{t,r}(w+1) = A_r(w) \times (-\omega_{t,r}(w) \times \delta - G_{t,r}(w) * \alpha)$ |
| Else if $w \leq 2 \frac{X}{2}$ and $w > \frac{X}{4}$ |
| $S_{t,r}(w+1) = A_r(w) \times p_{(x_{1,r})} \times EF(w) \times \alpha$ |
| Else if $w \leq 3 \frac{X}{4}$ and $w > 2 \frac{X}{4}$ then |
| $S_{t,r}(w+1) = \frac{1}{(1 - rand + rand^{\frac{\kappa}{D(\kappa)}})} [S_{t,r}(w+1) - 2randG_o(\gamma) + rand \times G_{o-1}(\gamma)] \times G_{t,r}(w) * \alpha$ |
| else |
| $A_r(w) - \omega_{t,r}(w) \times \delta - G_{t,r}(w) * \alpha$ |
| End if |
| End for |
| End while |
| Identify the ideal solution |

Here, the LRSA is used to adjust the weights and biases of DMN to evaluate the best cost estimation results.

5. Results and discussion

The results and details of LRSA_DMN for cost estimation is analyzed in below section.

5.1 Experimental setup

LRSA_DMN is tested using the MATLAB tool running on a Windows 10 operating system.

5.2 Dataset description

The final project accounting data at a real estate company in Jiangsu is the dataset used here. The final accounting information for 240 completed residential projects built by the Jiangsu real estate companies in past three years are obtained. After removing the irrelevant information and adding, 227 sets of the valid training samples are attained. The LRSA_DMN system uses three metrics for evaluation:

MSE: MSE is a statistic obtained by subtracting the expected value from the predicted value. Furthermore, the MSE expression can be calculated using equation (11).

RMSE: RMSE is calculated by getting the MSE square root.

$$RMSE = (Fit_{\min})^{\frac{1}{2}} \tag{26}$$

where, Fit_{\min} is MSE.

Accuracy: This metric measures how well the expected values compare to the predicted values. Also, the mathematical representation of the accuracy test is as follows:

$$Ac = \frac{E^{po} + E^{ne}}{E^{po} + E^{ne} + Z^{po} + Z^{ne}} \tag{27}$$

where, E^{po} and E^{ne} are true positive and negative. Z^{po} and Z^{ne} is false positive and negative.

5.3 Sample outcome

Figure 3 depicts results of LRSA_DMN used to estimate the building cost of measuring and operating each project during the test period.

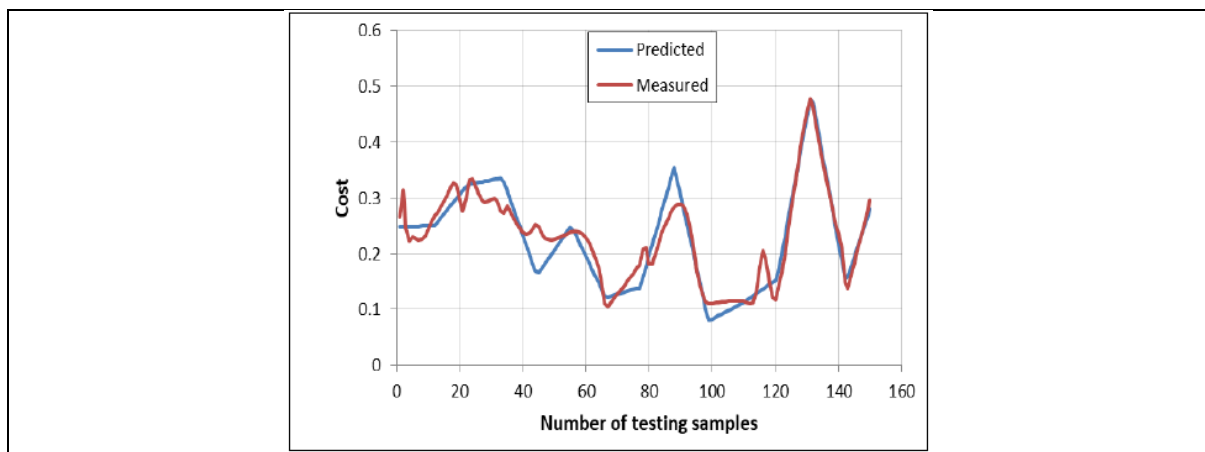


Figure 3. Estimated output

5.4 Comparative methods

The performance improvement of LRSA_DMN is evaluated by comparison with standard methods, like PCA [1], ANN-PSO [4] and MOGSO [7].

5.5 Comparative assessment

Figure 4 shows the comparative evaluation of LRSA_DMN using different metrics. Figure 4i) shows the performance evaluation of LRSA_DMN after changing the training data %. For 60% of the training data, LRSA_DMN produces an MSE of 0.3, PCA of 0.346, ANN-PSO of 0.324, and MOGSO of 0.319. Therefore, for MSE, LRSA_DMN performs better than other examined methods in terms of percentages of training resources. The RMSE analysis is shown in Figure 4ii). If the percentage of training data is 70, the RMSE value measured by LRSA_DMN is 0.452, and the RMSE value of traditional methods is 0.491, 0.48, and 0.461. Therefore, if you compare the accuracy of the current method and the developed method, it is 0.662, 0.676, 0.701, and 0.738 with a training data percentage of 60. Additionally, the LRSA_DMN performance is enhanced by 7.6%, 6.2%, and 3.7%. Therefore, the results are better for the construction cost estimation. The results show that LRSA_DMN is a good application to estimate the price. For construction project cost estimation, the LRSA_DMN is suitable for initial construction estimation.

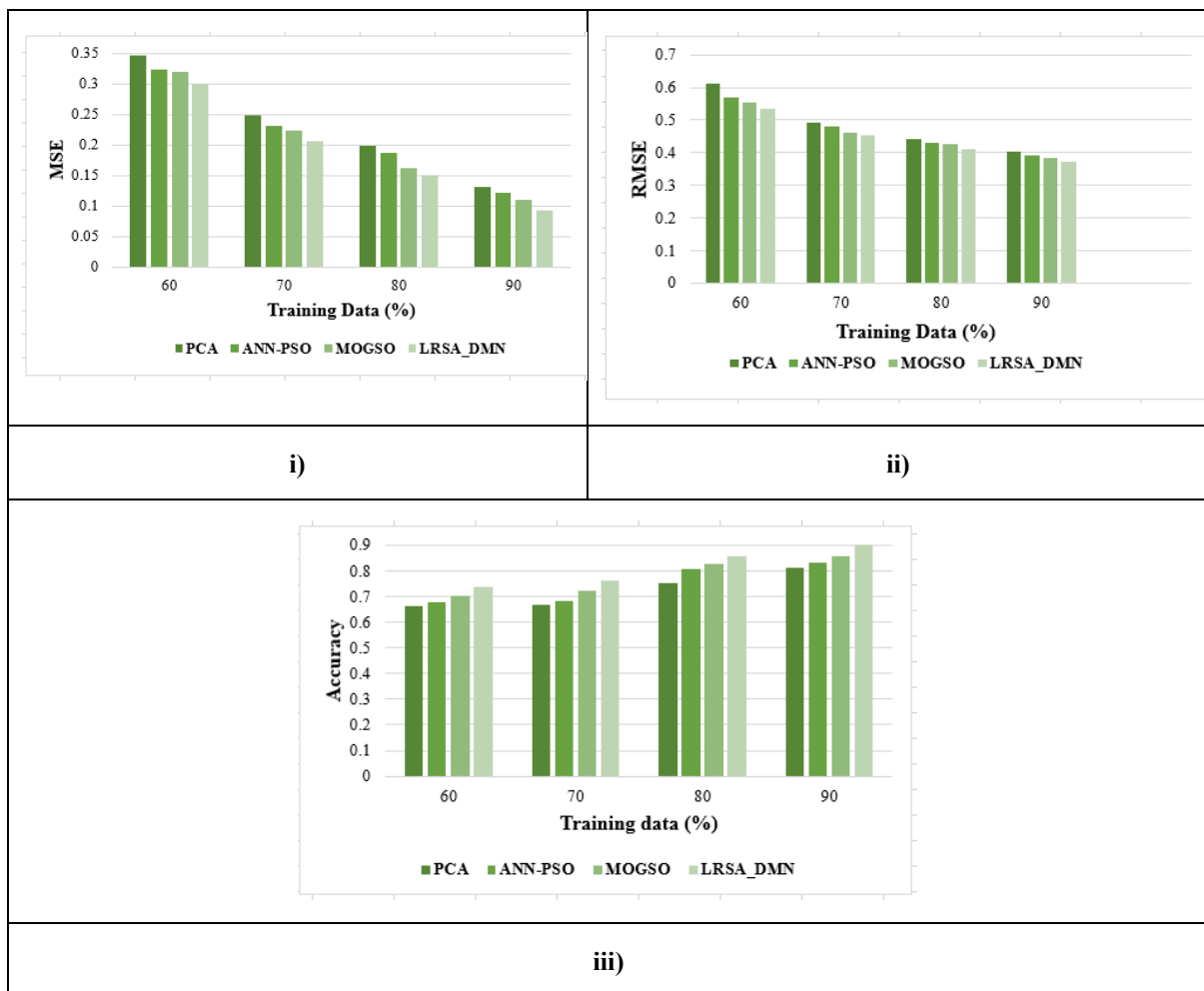


Figure 4. Comparative evaluation of LRSA_DMN, i) MSE ii) RMSE iii) Accuracy

5.6 Comparative Study

Table 1 compares LRSA_DMN in terms of evaluation methods. The MSE, RMSE and the accuracy values of LRSA_DMN are 0.092, 0.371 and 0.907, respectively. Similarly, other methods such as PCA, ANN-PSO, and MOGSO achieve MSE values of 0.132, 0.1212, and 0.109, RMSE values of 0.401, 0.392, and 0.382, and accuracy of 0.813, 0.832, and 0.854, respectively. The table below shows how LRSA_DMN achieves higher accuracy than PCA, ANN-PSO, and MOGSO. LRSA with DMN parameters is outperforms other models using accuracy, so LRSA_DMN is accurate. At the same time, the error of the previous model is controlled, so that the LRSA_DMN is very good. It is seen that the cost estimation model for high-rise residential project has better performance than LRSA_DMN using prediction accuracy and error control.

Table 1. Comparative discussion

| Metrics | PCA | ANN-PSO | MOGSO | LRSA_DMN |
|-----------------|-------|---------|-------|--------------|
| MSE | 0.132 | 0.1212 | 0.109 | 0.092 |
| RMSE | 0.401 | 0.392 | 0.382 | 0.371 |
| Accuracy | 0.813 | 0.832 | 0.854 | 0.907 |

6. Conclusion

This paper proposes LRSA_DMN for cost estimation during manufacturing. Here, DMN is a DL algorithm that is used to determine the costs. In addition, LRSA is an integration of two optimization algorithms, RSA and LBO, adjust DMN weights to accurately determine costs. RSA has benefits of low time complexity, fast convergence speed, and the effective global search. In addition, LBO is associated with updating the group positions (two different ways) and ignoring the worst members, which increases the search speed. Therefore, the estimation results are better using LRSA. In addition, the test results show that LRSA_DMN performs better in terms of MSE, RMSE, and accuracy, namely 0.092, 0.371, and 0.907, respectively. In future, Developers use big data analysis to identify trends, optimize resource allocation, and accurately determine project costs.

References

- [1] T. Q. D. Pham, T. Le-Hong and X. V. Tran, "Efficient estimation and optimization of building costs using machine learning", *International Journal of Construction Management*, vol.23, no.5, pp.909-921, 2023.
- [2] Xiaojing Ding and Qiulan Lu, "Construction cost management strategy based on BIM technology and neural network model", *Journal of Intelligent & Fuzzy Systems*, vol.40, no.4, pp.6669-6681, 2021.
- [3] V.B. Chandanshive, and A.R. Kambekar, "Estimation of Building Construction Cost Using Artificial Neural Networks", *Journal of Soft Computing in Civil Engineering*, vol.3, no.1, pp.91-107, 2019.
- [4] Mohammed H. Ali, and Abbas M. Abd, "Using of an Artificial Neural Networks with Particle Swarm Optimization (ANN-PSO) Model in Prediction of Cost and Delay in Construction Projects", 2021.
- [5] Tarq Zaed Khalaf, Hakan Çağlar, Arzu Çağlar, Ammar N. Hanoon, "Particle Swarm Optimization Based Approach for Estimation of Costs and Duration of Construction Projects", *Civil Engineering Journal*, vol.6, no.2, pp.384-401, 2020.
- [6] Dan Ye, "An Algorithm for Construction Project Cost Forecast Based on Particle Swarm Optimization-Guided BP Neural Network", *Scientific Programming*, pp.1-8, 2021.
- [7] Duc Hoc Tran, "Optimizing time–cost in generalized construction projects using multiple-objective social group optimization and multicriteria decision-making methods", *Engineering, Construction and Architectural Management*, vol.27, no.9, pp.2287-2313, 2020.
- [8] Nabil Ibrahim El-Sawalhi and Omar Shehatto, "A Neural Network Model for Building Construction Projects Cost Estimating", *Journal of Construction Engineering and Project Management*, vol.4, no.4, pp.9-16, 2014.
- [9] Sanaz Tayefeh Hashemi, Omid Mahdi Ebadati, and Harleen Kaur, "Cost estimation and prediction in construction projects: a systematic review on machine learning techniques", *SN Applied Sciences*, vol.2, no.10, pp.1703.2020.
- [10] Claudius A. Peleskei, Radu A. Munteanu, and Radu Munteanu, "Risk Consideration and Cost Estimation in Construction Projects Using Monte Carlo Simulation", *Management (18544223)*, vol.10, no.2, 2015.
- [11] T Gopalakrishnan and R Saravanan, "Cast Off expansion plan by rapid improvement through Optimization tool design, Tool Parameters and using Six Sigma's ECRS Technique", In *IOP conference series: Materials science and engineering*, vol. 183, no. 1, pp. 012016, IOP Publishing, March 2017.
- [12] Venkatachalam Senthilkumar and Koshy Varghese, "Structured Methodology to Formulate Drawing Dependency Structure Matrix for Construction Design", *Architectural Engineering and Design Management*, vol.5, no.4, pp.225-248, 2009.
- [13] Joseph Ahn, Sae-Hyun Ji, Sung Jin Ahn, Moonseo Park, Hyun-Soo Lee, Nahyun Kwon, Eul-Bum Lee, Yonggu Kim, "Performance evaluation of normalization-based CBR models for improving construction cost estimation", *Automation in Construction*, vol.119, pp.103329, 2020.
- [14] Alexander Layer, Erik Ten Brinke, Fred Van Houten, Hubert Kals and Siegmar Haasis, "Recent and future trends in cost estimation", *International journal of computer integrated manufacturing*, vol.15, no.6, pp.499-510, 2002.
- [15] H. Murat G€unaydın, S. Zeynep Dogan, "A neural network approach for early cost estimation of structural systems of buildings", *International journal of project management*, vol.22, no.7, pp.595-602, 2004.

- [16] Sevgi Zeynep Doğan, David Arditi, M.ASCE, and H. Murat Günaydin, "Using Decision Trees for Determining Attribute Weights in a Case-Based Model of Early Cost Prediction", *Journal of Construction Engineering and Management*, vol.134, no.2, pp.146-152, 2008.
- [17] Abualigah, L., Abd Elaziz, M., Sumari, P., Geem, Z.W. and Gandomi, A.H., "Reptile Search Algorithm (RSA): A nature-inspired meta-heuristic optimizer", *Expert Systems with Applications*, vol.191, pp.116158, 2022.
- [18] Jain, Y.K. and Bhandare, S.K., "Min max normalization-based data perturbation method for privacy protection", *International Journal of Computer & Communication Technology*, vol. 2, no. 8, pp.45-50, 2011.
- [19] Sagitov, S., "Weak convergence of probability measures", 2020.
- [20] Bootstrap framework taken from, "<https://machinelearningmastery.com/a-gentle-introduction-to-the-bootstrap-method/>", accessed on December, 2022.
- [21] Sun, W., Su, F. and Wang, L., "Improving deep neural networks with multi-layer maxout networks and a novel initialization method", *Neurocomputing*, vol.278, pp.34-40, 2018.
- [22] Safiri, S. and Nikoofard, A., "Ladybug Beetle Optimization algorithm: application for real-world problems", *The Journal of Supercomputing*, pp.1-50, 2022.