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Time and Cost Estimation of Pre-Fabrication Construction by Using ANN

Mahiuddin Khan¹, Abhijit Mangaraj²

¹Research Scholar, ²Assistant Professor, Gandhi Institute for Technology, Bhubaneswar, Pin- 752054^{1,2}

Abstract: The ANN has received a lot of attention recently because of its ability to tackle both quantitative and qualitative challenges in the building sector. This paper proposes using the ANN to forecast the Cost Performance (CP) and Time Performance (TP) of the prefabrication process in a building project. In this case, various percentages of prefabrication contents are added to the building, and estimated duration, real duration, estimated cost, and actual cost are utilised as inputs to the ANN process.

Keywords: Time and cost estimation, ANN, construction, pre-fabrication

I. INTRODUCTION

In this study, an Artificial Neural Network Fitting Tool (nftool) with a typical multilayer feed forward neural network trained with the back-propagation learning method is employed. Despite the vast size of the data collection, training is done automatically using scaled conjugate gradient in this programme. Furthermore, mean squared error and regression analysis are used to assess performance. The values supplied to the network are automatically mapped with a value ranging from -1 to 1. The 36 data are randomly divided into 30 for training and testing, while another 6 data are evaluated for validation that are not included in the training and testing procedure. The training data is utilised to fine-tune the network weight based on mistake.

The validation data are used to generalise network as well as to end training when generalisation stops improving. Testing data has no impact on training & serves as an independent indicator of network performance during & after training. When network fails to operate effectively after training, neurons in hidden layer are strengthened. When generalisation stops improving, as shown by an increase in mean square error of validation data samples, training is automatically terminated.

Due to varied initialization of connection weights and different beginning conditions, training several times yields diverse outcomes. In a gradient descent approach, the back propagation technique is meant to decrease an error between the actual output and the desired output. The mean squared error is defined as average squared difference b/w normalised outputs & targets and is provided in Equation (1); zero indicates no error and greater than 0.6667 indicates greater error.

$$\text{Mean squared error} = [\Sigma(O_{pi} - t_{pi})^2] / 2 \dots\dots\dots(1)$$

Where O_{pi} and t_{pi} are the actual and desired outputs of node I, when applying the input vector p into the network

In prefabricated projects, the nftool is used to anticipate the best time and cost. The ANN design employed in this study, as shown in Figure 1, contains an input layer with five inputs, including percentage of prefabricated content, estimated cost and time, actual cost and time, and a sigmoid activation function, and one hidden layer with neurons and a sigmoid activation function.

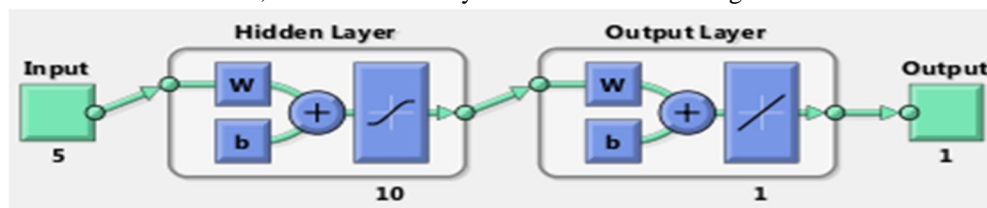


Figure 1 Artificial Neural Network Structure

It has a multi-layer neural mechanism that houses three distinct levels, namely input, hidden, & output layers. Brain networks are coupled with biological neural networks to accomplish duties collectively and independently by the units, with no discernible demarcation of subtasks to which varied units are assigned. The phrase "neural network" is commonly used to refer to models used in statistics, cognitive psychology, and artificial intelligence. This contains a significant ANN structure, as well as a single shrouded layer & 1-20 hidden neurons. In statistics report, ANN equation F_i represents an input layer parameter & O_i represents an output layer parameter.

The artificial neural system is a highly optimised computing technology tasked with replicating the neuronal architecture and functioning of the human cerebrum. It serves as a home for an interconnected architecture of fraudulently supplied neurons, as well as a channel for data transmission. The data sets are classified based on structure for recognising base sneak past by adjusting weights &, which are constantly updated with ultimate purpose of computing movement of input limitations. The weights α and β would have many restoration methods like as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) algorithm which are easily developed to appear at perfect weights of the objective capability, and they provide the difference between the test and the estimated values for enhancing.

Validation was performed utilising both the same data source and an external data source. There were 36 data sets available. The ANN model was trained using 30 different data sets. To do same data source validation, 6 data sets were chosen from the 30 data sets and tested to see if the model functioned as expected. Following that, 6 more data sets were employed to evaluate the trained ANN model for validation utilising external data source validation.

II. LITERATURE REVIEW

Jui-Sheng Chou and Julian Pratama Putra Thedja (2017) suggested a new classification system that combines swarm and meta-heuristic intelligence, i.e., a smart firefly method, and a least squares support vector machine. Benchmark functions were utilised to validate smart firefly algorithm's performance optimization.

According to Darwin Princy and Shanmugapriya (2017), power of fuzzy logic techniques can be very useful in productivity problem environment because their ability to represent problem in natural language may provide tool to investigate how human experts estimate probability of effect on productivity in real-world construction projects. When root causes of productivity issues are identified, they may be prevented or minimised.

In two real projects, VPS Nihar Nanyam et al. (2017) established a cost analysis methodology for precast technology & evaluated time & cost aspects of precast buildings vs. traditional construction. Precast technology has achieved time savings of 20-35 percent as compared to traditional technique of construction. Cost comparison, on the other hand, reveals a massive cost variance when compared to traditional/conventional technique of construction.

Kabindra K. Shrestha et al. (2016) used a mathematical model to construct a tool for estimating contingency cost of a road maintenance contract. A contingency cost is typically included in a project to cover change orders that may be created during the construction phase for a variety of reasons, such as unanticipated situations, design flaws, & scope modifications. The cost of change orders will be adequately controlled throughout the construction phase if the contingency cost is precisely assessed during the contract's procurement phase.

Ahmed Senouci et al. (2016) investigated cost overruns & delays in Qatari public building projects. The Qatar Public Works Authority offers data on 122 Qatari public construction projects. The analysis of variance technique was used for data analysis & inference.

Borja Garca De Soto & Bryan T. Adey (2016) discovered that combining artificial intelligence approaches with traditional procedures is a suitable way to produce estimations of the resources necessary in a building project, such as the quantity of construction material quantities required.

Nataa Praevi et al. (2015) claimed that optimising construction time and cost is linked to the cost of events and the total cost of project realisation. All activities are considered, including length, direct and indirect costs, project completion time, and activity relationships. The PSO approach is used to solve this nonlinear issue. Improved approaches for time and cost optimization are produced using appropriate tools and the scope of a MATLAB programming system.

Gopal Naik et al. (2015) used ANN to examine time & cost required in a major road building project. The necessary data were gathered from two successfully completed highway road projects, and the models were trained, tested, and verified using MATLAB R2013a software.

III. TIME AND COST ESTIMATION BY ANN

The ANN structure is used for training using known data, and this is the first stage in the prediction process. The better value achieved in ANN structure optimises structure's weight. Various optimization strategies are used to attain optimal weight of construction. If acquired results are not satisfactory, training phase is repeated in order to alter structure to an appropriate level for predicting output. Once acquired error values b/w output of real values & predicted values are near to zero, developed model is used to forecast unknown values in input & to optimise time & cost of operation.

The suggested work's findings are accomplished utilising the MATLAB 2019a working platform, with system configuration of i5 processors & 4GB RAM, and the estimation is done using ANN procedure. Thus, the Graphical User Interface (GUI) is developed by employing the aforementioned system setup to achieve the proposed ANN model's findings.

Figure 2 displays proposed Graphical User Interface, which is a human-computer interface, or a system that allows humans to connect with computers in order to make better decisions. It employs windows, icons, & menus that can be navigated using a mouse and, in certain circumstances, a keyboard. A window is a rectangular portion of screen that may display its contents, such as a programme, icons, a text file, or a picture, seemingly independently of rest of screen. An icon in a graphical user interface is a little picture or symbol that represents a programme or command, a file, a directory, or a device.

In the graphical user interface, commands are given by 1st moving a pointer on screen to or on top of icon, menu item, or window of interest in order to select that object with a mouse, trackball, or touchpad. Icons and windows, for example, may be moved by dragging or moving mouse with held down, & items or applications can be accessed by clicking on their icons. Furthermore, GUIs enable users to fully exploit modern operating systems' powerful multitasking capabilities, i.e., ability for multiple programmes &/or multiple instances of single programmes to run concurrently, by allowing such multiple programmes &/or instances to be displayed simultaneously. As a result, there is a significant gain in computer flexibility, as well as an increase in user productivity due to better decision-making.

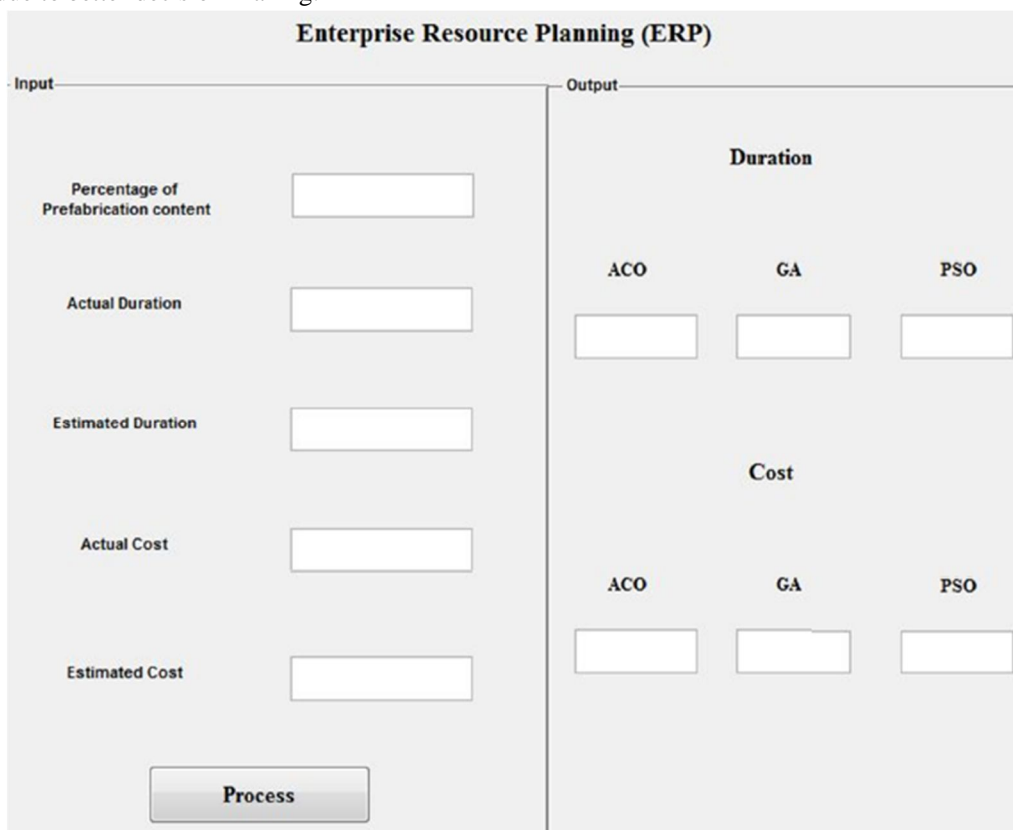


Figure 2 Graphical User Interface

As input data, the percentage of prefabrication content, actual duration, expected duration, actual cost, and estimated cost of the project are utilised to determine the estimated optimal outcomes of time and cost performance as output. Thus, utilising the ANN, the characteristics of the prefabrication technology in the building process, such as cost performance and time performance, are derived. The PSO algorithm in the artificial intelligence network neatly accomplishes the exciting job of discovering optimal solutions. In other words, as compared to the other two algorithms, GA and ACO, the differential error between the real-time output and the obtained output from ANN in the PSO is nearly equivalent to zero. As a consequence, the relevant output is assessed using the performance metrics in the error graphs of testing data presented in Figures 3, 4, 5, and 6.

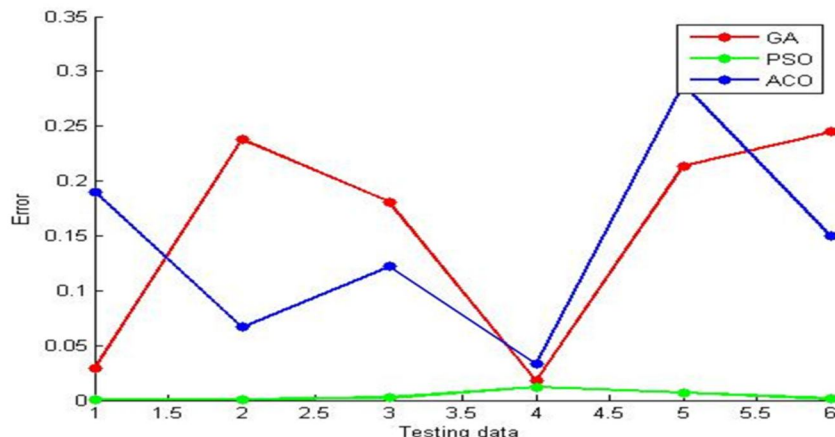


Figure 3 Error Graph for Time Performance with Different Algorithms of Same Source Data

Figure 3 depicts an error graph for the time performance of the prefabrication technology process when various algorithms are used. When the suggested method's minimum error value with the beginning data is compared to the ACO, the difference is 18.95 percent, & for GA, it is 1.9965 percent. The error value is determined using the output results, and the ANN process value is also anticipated. Figure 4 depicts the error graph for cost performance for various optimization strategies. The least error value of the cost performance is also obtained in the PSO process for the different testing input data values in this testing error graph.

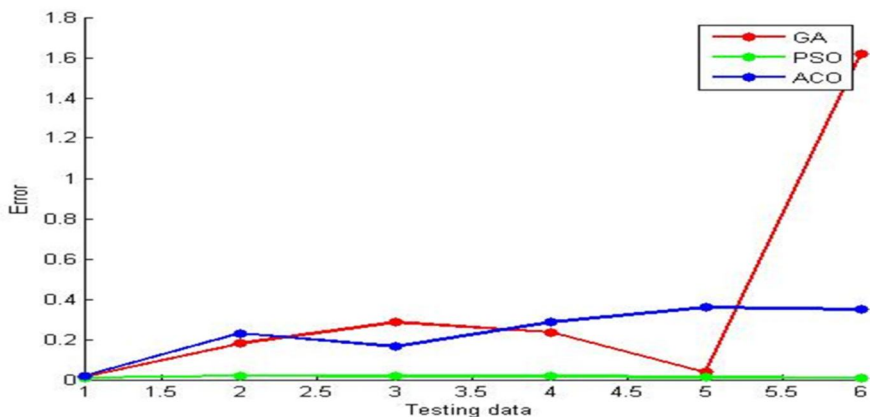


Figure 4 Error Graph for Cost Performance With Different Algorithms

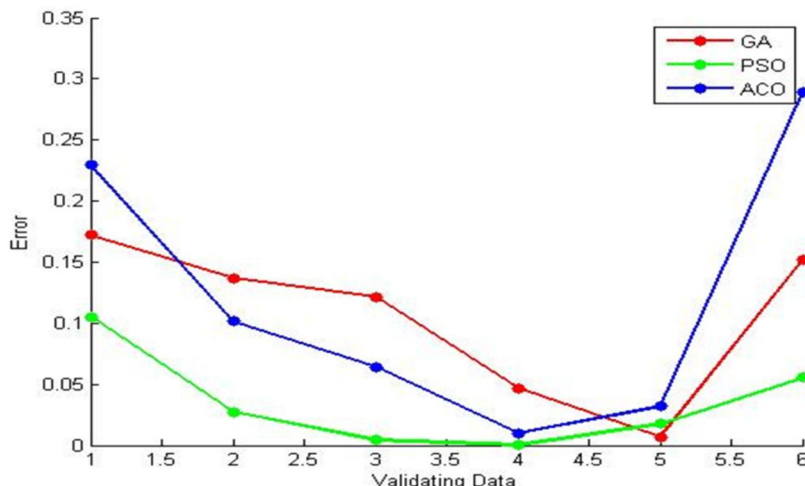


Figure 5 Error Graph for Time Performance With Different Algorithms of External Data Source

Figures 5 and 6 depict error graphs for time and cost performance with various Algorithms. The PSO algorithm produces the best optimal solution during the testing and validation processes. As a result, the suggested model is verified.

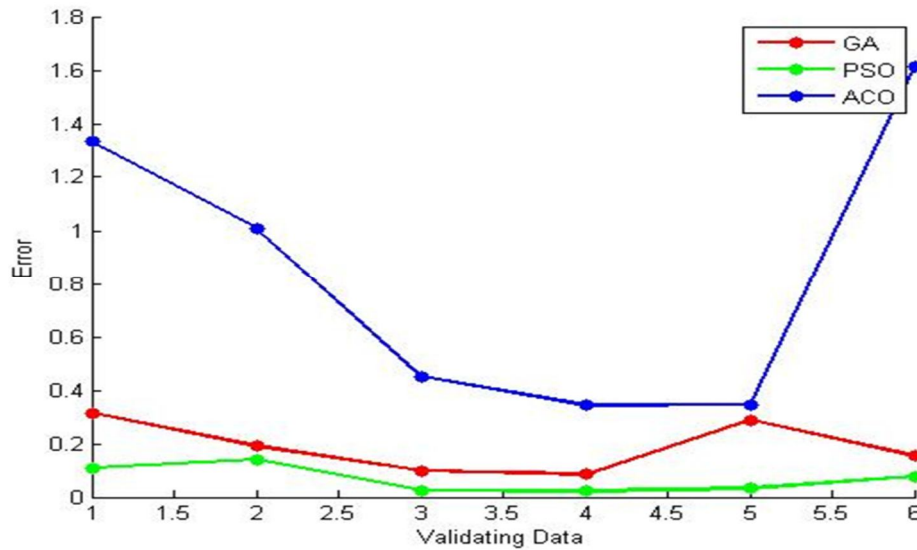


Figure 6 Error Graph for Cost Performance with Different Algorithms of External Data Source

IV. CONVERGENCE GRAPH

The convergence graph is depicted with iteration represented by X-axis & fitness represented by Y-axis. The convergence graph is constructed to demonstrate the iterative nature of time performance and cost performance solutions throughout the training process, and it might display error near zero obtained via iteration. Data from projects 1 to 30 are utilised as training datasets.

Figure 7 depicts the convergence graph of the prefabrication technique performance parameters for building, as well as the fitness values. The graphs depict the performance analysis parameters of fitness graphs based on iterations of GA, PSO, & ACO by varying weights from -500 to 500. As a result, the error values for the proposed ANN model are computed. Fundamentally, the graph addresses the PSO process by providing the least fitness with the most iterations. The convergence graph shows that the PSO algorithm achieves the lowest error, which is 0.5397 in the 92nd iteration.

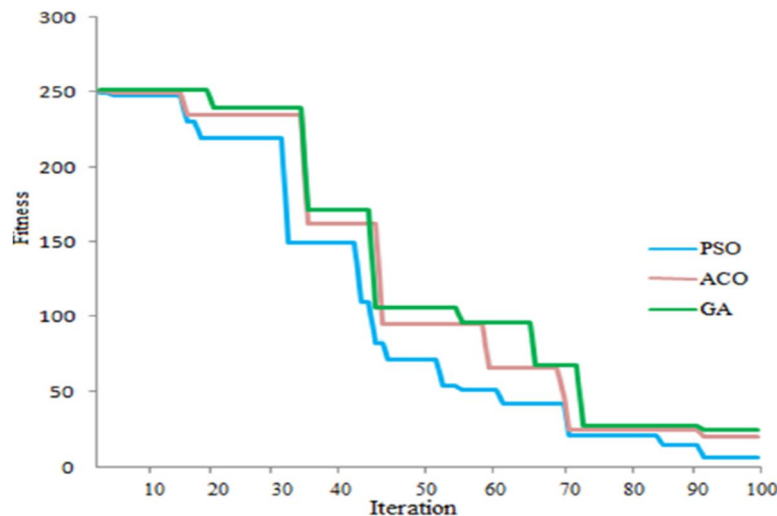


Figure 7 Convergence Graph

The suggested method's minimal error value is compared to GA and ACO. The average error difference is 77.55 percent, while the ACO approach has a difference of 78.57 percent. The behaviour of convergence graph during initial iteration reveals that fitness value is high based on algorithm's objective function, and then error values are gradually minimised or lowered. As can be seen from the graph, the results of the PSO approach efficiently provide the perfect fitness values.

V. CONCLUSIONS

The key benefits of this architecture are its interoperability and connectedness to the outside world via this Graphical User Interface (GUI)-based method. As a quantitative validation for the final choice, the input values may be altered, and the related outputs can be assessed for optimal criteria. This is why the model is being provided in this study. The primary problems of this model are the relatively large amount of effort and time that must be committed, and basic programming expertise is required for the model's creation. It should be improved further to ease the entering of input parameters and to provide the best possible outcomes for construction management success.

Thus, the error for the same data source is 0.55 percent as an average error of time performance, 1.25 percent as an average error of cost performance, and 3.51 percent as an average error of time performance, 4.89 percent as an average error of cost performance. In both cases, the inaccuracy is less than 5%. The results reveal that employing the trained neural network for validation using the same source data and an external data source, the outputs are in good agreement with the actual projected outcomes. As a result, the train ANN is useful for estimating the time and cost of prefabrication construction. As a result, the model is verified with the help of an external data source of six datasets that were not previously utilised in the training and testing procedures of the same source data.

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