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Implementationof Artificial Neural Network for Recognition of Factors InfluencingLabor Production Rates for Concreting Activities– A Review

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***Abstract*: *Construction projects globally is considered to be multifaceted in nature. This complex work involves estimates of labor production rates during the planning as well as in the execution phase of the project. These estimates are habitually carried out by experienced personnel based on his/her experience, may sometimes not have the means to discern the controlling factor factors affecting the production rates. There are various trends in the soft computing techniques for identification of labor production rate in construction, and one being associated with Artificial Neural Networks (ANN). The current study emphasises on critical literature review on factors likely to affect the productivity rates for concreting activities like reinforcement installation, formwork installation and concreting placement and also some of the other industrial activities.*

Keywords:Artificial Neural Networks (ANN), Back Propagation and LaborProductivity.*

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I. Introduction

One of the important facets for an efficacious construction project is to groundwork an accurate estimate, which in turn impact issues ranging from project feasibility to profitability. A milestone for accurate estimate is reached by determination of cost of the labour, which is in turn reliant on determining the expected labour productivity. Labour productivity estimate is often evaluated by an individual by means ofanamalgamation of analytical techniques and personal judgement. Experience and knowledge of construction activities are combined with historical information and detailed work studies to estimate labour productivity[1]. Since, the subjective nature of work the drawback of the current method to investigate productivity are inconsistent and often leads to improper judgement. As experience and knowledge exists with the estimator, who can sometime in exceptional cases not have proper assimilation of the work and perhaps not have means to acknowledge the existing controlling factors influencing productivity or may possibly not have expedientto correctly quantify these influential factors[1].

As estimates of the labor production rates is solitary crucial parameters in the construction industry, which is not only required during planning phase but also during the execution phase, it's important to groundwork what factors affect the production rates for different construction activities. Various machine learning (ML) techniques are available through the medium of which the factors likely to distresslaboroutput rates for different activities can be determined, and one being associatedwith is the artificial neural network (ANN). The prominence of this article is to review application of ANN in the construction industry, particularly in the field of construction engineering and management, so viewers are suggested to refer[2] forthe details of the various ML techniques. This article specifically emphasises on output rates of labor for construction activity and industrial activity. An overview of ANN is brief in the sectionII of the article, then in the succeeding sectionIIIdefinition of labor productivity, for section IVANN in civil engineering is discussed, and subsequently in section Vaninformativeliterature review on factors affecting labor production rates and finallyin section VIconclusion of the articles.

II. An Overview of Artificial Neural Networks

The fundamental concept of working of an artificial neural network (ANN) is grounded on functioning of a human brain[3]. As the human brain acquires knowledge from experience over the period of time from a huge set of memories likely, the artificial neural networks work in a similar manner by virtue of learning algorithm and with experience. A brief explanation of the conceptual idea of neural networksisinitiatedby[4]book titled, '*Neural Networks A Comprehensive Foundation*'.

The following definition of neural network in view of an adaptive machine is part of[4], chapter 1, pp2 which states NN, "As *a singular processing unit which consists of an immensely parallel distributed processor, having a natural tendency of storing the investigational information and availing it for use. It bearsa resemblance to brain into two aspects: i] because of the network organization (architecture) the knowledge is acquired through learning process, and ii] internal connection among the neurons helps in storing the experimental knowledge*."

The fundamental structure of an ANN model consists of three junctions i.e., input, followed by the hidden and finally the output. The information is processed staring from the input junction to the hidden junction. Depending upon the specific purpose of the model to run the quantity of hidden units may vary. The signal is then proceeded on to the output junction through the hidden junction.

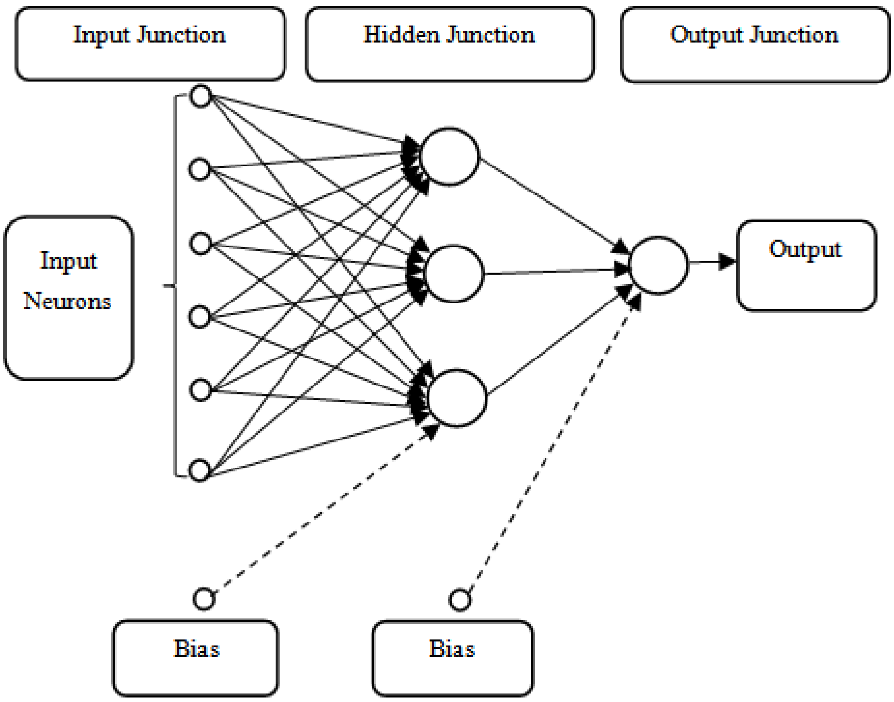

Fig.01: Fully connected feedforward network with one hidden layer and one output layer.

One of the common types of the neural network is the multilayer feedforward network (MLFF). A detailed review of MLFF networks is depicted very well in[5]. Fig. 01 depicts an MLFF network, whichconsists, six inputs neurons (processing elements PE) depending on the statistical data to be processed. Each of the neurons is multiplied by its connection weights and then passed through the hidden junction. An external bias is applied to measure the input being processed in the next proceeding layer i.e., (through the input and the hidden junction). If the quantity of hidden unit is greater than one, the connection weights are multiplied several times and summed followed by the activation function which limits the output generated by the network until it lastlyarrives to the output layer. Once the data has reached the output layer, it is again multiplied by the connection weights and summed to produce the desired output.

III. Construction Labor Productivity Definition

Productivity in modest term is defined as a ratio of unit output per given unit input. The output measured vary depending upon the purpose which is to be determined and also the various inputs provided to generate the required output. For example, for a hydraulic turbine the overall efficiency is defined as 'a ratio of power generated by the shaft of the turbine to the power provided by the water available at the inlet of the turbine'[6]. Here the productivity of the turbine in terms of power is obtained considering at the inlet of the turbine to have water storage in terms of water power i.e., water head and at the outlet in terms of shaft power, i.e., rotation of the shaft in (RPM). Both the inlet and outlet have same measure of units.

But for construction productivity of laborit can be measured by a variety of different measures depending upon its application for the various areas of construction[7]. Also, the definition of productivity changes depending upon the objective of measurement and available of the statistical data for analysis[8]&[9].

There is no solitary accepted definition for productivity worldwide, just because for a similar taskwork the measures of productivity taken by different ways by diverse people making the resulting productivity not directly analogous[9]. For each activity in construction is measured distinctively. Therefore, it is necessary for consideration of all influential factors likely to affect the productivity rates and the inter-relation among the factor the produce the desired output with its defined unit of measure. Thus, these influential factors are characterized into two parts: quantitative and qualitative[7].

Construction labor productivity has always be contained to the important topic amongst the researchers. A critical review on construction labor production rate showing performance of the labor for different activities over the past years, methodology adopted by several researchers to identify the factors affecting production rates, incorporating soft computing techniques for forecasting production rates and change in the trend in the area of research is depicted[10]. Productivity equation is expressed asratio of output/ expended work hour for completing the task is expended in the work of[7]. The taskwork involved was concrete pouring and concrete finishing for which output were measured in cubic metres and square metres respectively.Another performance measure for labor was given by[11] for reinforcement erection, formwork installation and concreting activity as ratio of product of crew size and duration for the work to total quantity. In which the productivity measure unit is (man x duration/ quantum of the work) i.e., tonnes for steel erection and cubic metre for formwork installation and concrete pouring activity. The authors strongly recommend the readers to analyse the objective to measurement and data required to be collected to perceive the required productivity rates measure.

IV. Ann In Civil Engineering

Anextensive amountofresearch papershas been published ever since 1989 after the first publication in the area of interest for construction/structure was carried out by[12]. Various research articles of ANN in different fields of civil engineering like construction management, geotechnical engineering, transportation engineering, hydraulics and concrete technology are published in the subsequent years. For application of ANN in construction engineering management[13] and [14], for tidal wave forecasting, earthquake induced liquification [15], in the area of interest for geotechnical engineering[16]. Early cost prediction of building using ANN is well explained in [17], [18],[19] and [20]. Wave prediction for coastal region was developed by [21] wherein the authors explained wave heights up to 24 hours based on cautiously selected parameters from the previous seven days was used as strategical modeling. Time series wave prediction using two ML techniques i.e., Genetic Programming (GP) and Model Tree[22],in which researchers found GP had better forecasting values underlying the measures of coefficient of correlation, coefficient of efficiency and mean squared error.A critical review for various work of ANN in ocean engineering is depicted in[23], followed to which the author tries to explain his experience working with ANN.Prediction of waves in real time operation[24], where data for the wind were recorded rather than wave. Using Genetic Programming (GP) for the future 96 hours wave heights and average wave period were forecasted using the data observed. In transportation engineeringprovince, ANN is successfully implemented for evaluation of network improvement in transportation system[25],recent trends and ANN for improving highway infra system [26] and [27] respectively, implementation of ANN forimprovement in the transportation performance working condition[28]. One of the critical reviews for application of ANN in waste water treatment is specifiedin[29], where the authorsbriefs about the ANN model developed for Gold Bar Waste Treatment Plant (GBWTP) one of the extensive sewage treatment plant in Edmonton, Alberta (Canada). ANN has also been effectivelyfunctional for forecasting air pollution and flood forecast[30], in the succeeding year ANN model was developed for optimization of filtration for a water treatment plant (Elgin Area WTP) in terms of postfilteringparticles, i.e., optimal quantity entailed to achieve the particle count[31]. As persuaded from the different articles ANN is successfully implied for prediction of different model in the civil engineering field. This article emphasises on reviewing the labor productivity rates for concreting activities and some of the industrial production activity rates of labor using ANN.

V. Literature Review

A thorough literature survey was conducted for recognition of influences that contributes to result in making difference to labour productivity and ANN in the construction industry. Therefore, the following literature review is classified into following two categories: a) ANN for identification of labor productivity for different construction activity and/or industrial activity and b) ANN for recognition of factors likely to distress laboroutput rates for concreting activities.

A. ANN for identification of laborproductivity for different constructionactivity and/or industrial activity

Understanding the competitiveness and the menace associated with construction industry, persuaded a non-traditional tool for decision making[32]. Wherein the authors described Neural Networks as an add-on with the expert systems. A stepwise procedure for artefact of construction activities to draw into patterns is presented, followed with parameters likely to govern the design NN for any particular problem is briefed. Three years later[33] developed two approaches i.e. Percent Complete and Factor Model using 22 masonry data for forecasting labour productivity. Portraying a conclusion that FM (Factored Model) is more accurate with error range of 5% while the PC (Percent Complete) is consistent for 22 data but the error range is as high as 50%. Various tools are available to model the forecasting productivity for different construction activities. Aremarkthat neural networks are solitary commanding tools in soft computing for classification of patterns, optimization, function approximation and modeling is persuaded by[7]. The NN mimic the operation of brain. As the brain collects data, learns from previous memory and then judges for new similar situations, likewise the NN learns from different algorithm. The different NN are used by researchers for prediction of different activities in the construction industry. The basics of MLF and back-propagation learning algorithm is enlightened very well[5]. Also, the authors explained training and generalization of MLF NN with refinement of the standard back-propagation. Probability Inference Neural Network (PINN) model for steel piping works was utilized[34].With a perspective of historical data possesses significant data for prediction of labor output rates, shortfall of the inconsistency in the productivity measurements system and poor quality of storage of the historical data often leads to an intercepting a meaningful investigation of labour productivity. A total of 36 factors were identified to likely to affect the productivity. 119 records from over 66 projects were collected for NN. The PINN model included 81 input nodes, with 20 equally distributed output zones. Out of 119 data, 101 were used for learning and 18 for testing the network performance. While the NN model had 81 input nodes, 40 hidden nodes and 1 output. Both the NN model and PINN model were tested, and it was observed that the PINN model outpaced the NN model in terms of point forecast accuracy, which means the value predicted by PINN model were closer to the one given by the actual output. With a similar approach for pipe installation activity[35], discussed that ANN can be utilised to estimate the production rates of labor i.e., (labor/unit) for industrial activities. The authors discuss the efficiency multiplier for forecasting of the production rates, then constructing a two-stage ANN model for classification and prediction and comparison with the actual production values. A total of 27 completed projects for 39 pipe installation data were collected. Over 33 factors were identified under 9 subheads which includes: general project characteristics, site, labor, equipment, overall project difficulty, general activity, activity quantities, design and activity difficulty. Marking a conclusion that ANN can predict the reasonably accuracy of the production rates for pipe installation, and more precision in the results will be encountered if the model is trained with a greater number of data set. Seven years later after PINN model was developed for forecasting steel piping works,[36] used PINN and discrete-event simulation for steel drafting and shop fabrication estimation. For measuring the complexity to data acquisition of steel drafting and fabrication, a piece-by-piece approach was defined. A total of 17 factors: project type, work scope, contract type, piece of cloning, dynamic structure, fir proofing, special fall arrest provision, overall complexity, draft person qualification, crew size, client, engineers firm, engineering standards, administration, overtime, subcontracts and total work quantity for steel drafting and 6 factors: piece weight, piece length, number of cut-outs and fitting, fitter skill level and working shift for steel fabrication were taken into consideration. A total of 59 data for steel drafting out of which 51 were utilised for training the network and 8 for validating, while for steel fabrication out of 131 data, 111 were utilised for training the network and 20 for validating the PINN model in *Neuroshell 2000*. After which the discrete-event simulation was prepared. From the study it is swayed that ANN could be efficaciously used for mapping complex relationship modeling of individual activities i.e., between productivity and influencing factors. Through the study[37]swayed a method of identification of parameters likely to influence the production rate of labor for finishing works of marble for cases like the residential, commercial and educational projects. Wherein, the authors collected data set of 150 from ten different projects in Iraq out of which 60% was used for training, 25% for testing and 15% for validating the model in the commercial tool *NEUROFRAME 4* program. The multi-layer back-propagation NN was utilised to develop the model with sigmoidal transfer function. Thereafter, it was concluded that the ANN could predict the labor output rates for marble finishing works with accuracy of 89.55% of coefficient of correlation and average accuracy percentage of 90.9%. The findings included age, experience and numbers of assist labour had a substantial effect on productivity.

B. ANN for recognition of factors likely to distress labor output rates for concreting activities.

A survey was conducted to identify factors affecting labour productivity in Canada for concrete formwork tasks[1], which consisted of conventional loose, and panel formwork for slabs, walls and columns, wherein they identified the factors which includes: crew availability, superintendent, weather, location, repetitive use and quantity[38]. The data collected for identification of factors included both subjective and numeric. In order for the subjective statistics to be deployed into ANN, it had to be transformed into numeric format. Various NN structures were experimented but they were dropped because they produced inaccurate results. Two problemswere identified: i] when prediction was wrong, they were not marginally wrong but significantly wrong, ii] one-point estimate of labour was not acceptable by estimators because of fuzzy nature of the problem. So, with many trials of the network architecture,the selected network was three-layer back propagation with fuzzy output layer, wherein the network sigmoid transfer function was utilized. There were 55 inputs nodes on behalf of 30 factors, 30 hidden nodes in one hidden layer and 13 output nodes. After, the model was prepared in *Neuralworks Professional II Plus Shell*, a case study was presented to 12 estimators related to similar work and they were asked to identify the labour productivity for a given of questionnaire for construction of formwork for foundation wall. Thereafter, the same inputs were given to the model prepared prior to this questionnaire. The model was not trained for the new set of questions. Wherein the model predicted 0.47 ± 5%, only two out of 12 estimators predicted correct productivity value (0.492 m-hr/ sq. ft. ± 5%).

A similar survey was exhibited in Iowa, United States of America for identifications of factors affecting labour productivity for concrete works which included concrete pouring, formwork and concrete finishing[7].An approach for quantifiable assessment of multiple factors on labor production rates based on neural networks and regression technique is swayed in the research work. Data wereretrieved for two years from 1992 to 1994 from eight buildings projects of a contactor. A total sum of 112 for concrete pouring, 76 for formwork and 46 for concrete finishing were collected on weekly basis points. A regression model was first created after which a parsimonious model was used to compare both regression and neural network model. T-statistic factor was used to compare the closeness of fit, and prediction performance of model with or without factor, where the criteria used to determine the significance of the factor in the model. Back-propagation algorithm was used and sensitivity analysis was performed to compare between the predicted and closeness-of-fit model. The factors affecting productivity identified were quantity, temperature, crew size, precipitation, humidity and overtime.

A couple of years short than a decade later after[7], a survey was carried for determination of factors affecting productivity for concrete pouring activity in developing country of Egypt[11]. A survey form was made to retrieve data for concrete pouring activities which included steel fixing, formwork task and concrete pouring activity. The factors were identified from past literature survey, after which the parameters were examined with five experienced project managers with minimum of 15 years of experience in the industry to finalize the survey form. 18 participants working in 6 different projects having experience of 5 to 10 years in construction industry were selected to collect 92 data set for the survey in similar nature of the work i.e. residential, commercial and industrial projects. The commercial tool used to translate the data into predicting value was *Neuro Solution 4 2001*. The learning algorithm for all the activities was feed-forward back-propagation with a hyperbolic tan function (tanh) transfer function. Through the training, testing and validation the results exhibited that productivity decreased by 65% for hot weather condition, followed to change in productivity +/- 20% depending upon degree of supervision, further average 50% increase in productivity with better skills of labour, twice shall be productivity for typical task work and increase in 30% productivity with degree of accessibility to the materials.

A field study determining effects of a set of variables on daily and/or short-term jobsite labour productivity using artificial neural network in Montreal, Canada[39].Nine parameters were identified[40], affecting labour productivity which included: temperature, relative-humidity, speed of the wind, precipitation in the locality, number of crew members, crew composition, vertical elevation of the work, classification of nature of work and construction techniqueutilized. Considering these parameters, a survey was conducted on job-sites in Montreal which had similar characteristic of work and constructed during same time to collect the real-time data directly from the site superintend for a tenure of 10 months. Total 221 data set were collected to develop a neural network model, out of which for training of the model 60% of the data set were used, while 20% for testing and the rest 20% for validation. The developed model which out-performed the rest of the model was the back-propagation NN. The commercial tool used was *MATLAB* and *Neuroshell 2*. From the developed model after training, testing and validating it was discovered that the developed model identified temperature as the most significant factor affecting productivity, then flowed by the height of the work expressed by floor level and type of the work.

In the same year,Self-Organizing Map (SOM) for determination of laboroutput rates for ready mixed concrete, formwork and reinforcement crew productivity and compared the results with ANN model was developed[41]. SOM is a ML technique which incorporates high dimensional data into low dimensional data without any loss of its topological relation of the data. It is grounded on unsupervised leaningwhere data are organised on the basis of similarity. The study was conducted in Turkey and the data for the study was collected for a tenure of two years starting from September 2006.A total of 144, 101 and 101 data were retrieved for concrete pouring, formwork and reinforcement activity respectively. The outliners from the data were eliminated using Box and Whiskas method mentioned in[42]. Factors identified were crew size,experience of the crew in particular, age, method of payment system, working hours for a week, daily work-hours, accommodation distance of the crew from the site location. Both SOM based 2-D model and ANN model were developed for assessing the performance of both the model. Concluding with the result that the SOM maps produce satisfactory model in clusters and prediction model is superior to similar ANN models developed.

In the following year, a method based on artificial neural network for estimating the required man-hours for formwork activity for buildings was developed in Istanbul, Turkey[3]. The factors identified by the authors were: total length of column, the entire length of beams, the total area of shear walls, the total slab area, the elevation of the building, floor-to-floor height of the building and the overall number of floors to be constructed. A total data of 613 sets compiled from 22 different building projects of similar nature have been used to develop the formwork productivity model[43]. The commercial tool utilized for the construction of the model was “FANN Tool” as being a segment of neural network library named “The Fast-Artificial Neural Network Library – FANN” having an open source access to all,[44].A total of 551 data set was utilized to develop the model, while 62 sets were randomly selected for testing of the model. For training of the network architecture, the algorithm used was back-propagation with sigmoidal activation function. The function was chosen as it had least RMS (Root Mean Square) error of 9.2% and maximum single error of 21.3%. the trained model was then tested with two live projects of similar nature. In first project the predicted value and estimated value had a total error of 5% of man-hour, while in the second project the total difference in man-hour calculated is 15%. In both the cases the values predicted by the prediction model was more precise than the estimating using Turkish Ministry of Public Works and Settlement (MP+S).

In the same year, a similar work was carried out for identification of production rates of formwork for beams for high rise structures in Malaysia[45]. Through the literature survey conducted factors affecting labor production rates were classified into two categories: management factors and site related factors. A total data of 84 observations from over 7 different projects in Malaysia were selected for data collection. Based on feedbacks given and using Severity Index as groundworkthe five influencing factors identified were: availability of materials and equipment, number of workers, site condition, weather and location of project. Then the coefficient of correlation was identified with the production rates with these factors, where independent variable was selected as the influencing factors and dependent variable was the production rates. After which the ANN model was developed using the total 84 data set. A k-fold validation technique was utilised where all of the 84 data sets were equally distributed into 10 equivalent parts. The optimum results were generated at 5-1-1 as input, hidden layer with 20 neurons and output layer respectively, utilising gradient descent with momentum BP with transfer function of hyperbolic tangent and sigmoidal function. The performance of the network was measured using MSE and average MSE. The following observations were drawn between the actual site and predicted value from ANN developedmodel as, 0.04366 hr/m² to 0.0471 hr/m² and 0.0392 hr/m² to 0.0487 hr/m² respectively.

Three years later a model was developed for labour productivity in Iran for works related to building foundations of gas, steam and combined cycle power plant projects[9].15 factorsaffecting labour productivity were identified which included proper coordination, efficacious means communication, appropriatescheduling, proper (Health, Safety and Environment for proper working) HSE program, technical superiority, apposite site layout, labour proficiency, adequateamenities and housing, inducement of labour; positive factors, deprived decision making ability, schedule compression, persistent change in orders given, deficiency in resources like materials, tools and equipment and inauspicious external condition; negative factor impacting on productivity[46]. After which the survey form which compiled altogether influential parameters stated above and the descriptive questionnaire was converted into numeric data with both positive and negative normalized numeric scale. The target population included completion of projects between April 2007 to February 2015 in Iran was 93. After which consideration of Cochran formula[47]based on 90% confidence and 10% error a sample size of 39 was approximated. The network used was multilayer feed-forward with back-propagation in commercial tool of *MATLAB*, with training function of scaled conjugate gradient back propagation called *trainscg* for early stopping and Bayesian framework in training function *trainbr*. The results of the network trained, validated and tested showed that Bayesian model to be more accurate than the Early Stopping method, which was conducted on two projects of similar nature but were not used prepare the productivity model for the same.

VI. Conclusion

In civil engineering many problems are encountered at several stages of constructionbecause of the complex nature of the work.Because of which the production rates of labor for different activities are hampered leading to levy the project with increment in time and cost. Also, for the reason that the multifaceted nature the factors affecting the production rates of the labor vary along with country, region, climate, work ethics, type of construction method employed and nature of work, technology deployed for the given work etc., which makes the work of the estimator or the constructor difficult to estimate the controlling factor affecting labor production rates for construction activities. ANN as a soft computing tool can be retrievedby the estimator or constructor to model the labor production rates for different construction activities and also to monitor controlling factors likely to hamper the productivity of the labor, and help the constructor and estimator to pay special attention on the matters of concern impeding production rate of the work by the labor. For any productivity measurement the author strongly recommends to define the objective of the performance measure, following to the which the statistical data retrieval procedure should be engaged.

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