

## Neural validation of FDBM Simulation for Formwork in construction

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### Abstract

In spite of considerable development in construction sector, the need of manual labour cannot be avoided. The India and other developing countries utilises intensive manual labour in building and infrastructures development. The methods used in these activities are either traditional or designed in a limited way. The present paper aimed to propose improvement in methods of performing these activities by developing mathematical simulation from data collected while the work was actually being executed in the field. Once the generalized model using all possible parameters developed, the weaknesses of the present method identified and improvement is possible. The main contribution of this paper is to develop the mathematical simulation of formworks placing sub activities in reinforced concrete construction and validate it with Neural Network prediction. Validation of the FDBM model is achieved by comparing with the Artificial Neural Network Prediction and found satisfactory.

**Keywords:** FDBM simulation, Formwork, Reinforced concrete construction, Reliability, sensitivity, ANN simulation

### 1. Introduction

Construction activities (Gunnar Lucko et al., 2009) though appears simpler in execution but the relation between inputs and outputs shows a very complex pattern (H.Schenck, Jr, 1961). All framed structures constitutes Reinforced Concrete work (Suhad M. Abd et al. 2008; Kwangseog Ahn et al.2000) as a major activity and the cost of formwork(E. Sarah Slaughter et al.,1997) found to be 30-60 % of cost of framed structure. The literature review indicate that though there are many work done by earlier researchers in the field of construction work simulation but no work had been done considering measuring the human energy input of manual work, workers anthropometric data, tools geometry, Work station data and materials properties. Thus this work becomes a novelty in

construction simulation and suggest improvement in the construction operation.

This paper explains the mathematical simulation (Anu Maria 1997) of manual formwork fixing sub activity. The purpose of developing model was to overcome the deficiencies in current method, for process improvement, process management and to reduce fatigue in the workers and musculoskeletal injuries (John Rasmussen et al.2003; Kwangseog et al. 2000, Rwamamara et.al, 1988). The approach has been motivated from principles of construction management and Method study in industrial engineering (S. Dalelae 1991; K.H.F.Marrel 1967).

The work of this paper explained in following steps.

I. Formulation of FDBM model

- a) Study of the present method of manual Formwork fixing,
- b) Identification of Causes and Responses,
- c) Mathematical approach selected and development of model.
- d) Interpretation of model

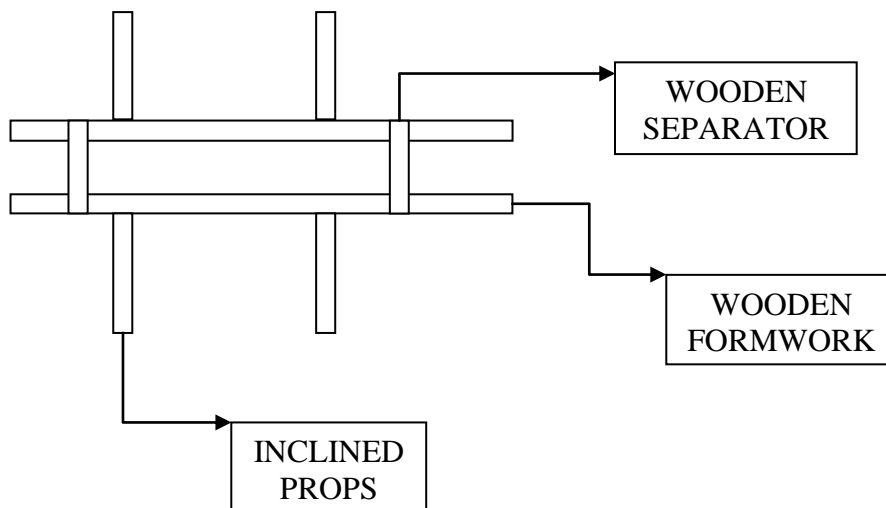
II. Results and analysis

III. Validation of model using Neural Network

**2. Formulation of FDBM model**

- a) Study of the present method of manual Formwork fixing,

Formworks are temporary structures, which are removed after concrete attains enough strength of a R.C.C. member. The formworks are built on site using timber planks and props for lateral supports at suitable intervals. The traditional timber formwork is preferred at common construction site and this is developed according to size and type of building components. Such as ground beam, beams supported from three sides, footings of columns, columns and slab forms.



**Fig. 1: Layout of work station of ground beam formwork**

In Figure 1 the work station of formwork construction has been shown, Here two number workers required for transporting planks, keeping in position and nailing. The two wooden frames kept vertically according to width of beam and they are kept apart by wooden separators and supported laterally with inclined wooden circular timber props.

b) Identification of Independent and Dependent variables:

Causes or dependent variables: The activity of formwork includes the workers data as input like anthropometric data, height, age and weight .The tools used in formwork are small hammer with one end as nail remover, Hacksaw for cutting timber planks and props there geometric dimensions are recorded as inputs as the each dimensions on varying influences the outputs. The workstation data such as size and nos. of planks and props with their dimensions and weight, size, diameter and nos. of nails required to fix a formwork and time required to complete a given size of form recorded. The materials properties such as hardness in Rockwell hardness no. and shear strength of wood used .The environmental data such as ambient temperature, wind speed and humidity influences the output of workers so they are also recorded.

**Dependent variables:** For the formwork operations, the dependent variables would be: i) the extent of work done ii) the human energy consumed and iii) the performance error in % of the required work.

**Extraneous Variables:** These are other parameters, which could not identified, as inputs would be considered as extraneous variables such as loss of human energy by other means, effect of enthusiasm and motivations in workers performing the activity.

**Table 1: Name of Variables, Symbols and Dimensional Equation of Variables**

Name of Variables	Symbols	Type of parameter	Units of measurement	Dimensional formula
Height of Worker 1	$h_1$	Independent	cm	L
Anthropometric data of Worker 1	$A_1$	Independent	cm	-
Age of Worker 1	$ag_1$	Independent	years	T
Weight of Worker 1	$wt_1$	Independent	kg	M
Height of Worker 2	$h_2$	Independent	cm	L
Anthropometric data of Worker 2	$A_2$	Independent	cm	-
Age of Worker 2	$ag_2$	Independent	years	T
Weight of Worker 2	$wt_2$	Independent	kg	M
length of Hacksaw	$lhs$	Independent	cm	L
average width of Hacksaw	$avwhs$	Independent	mm	L
thickness of Hacksaw blade	$thohsb$ mm	Independent	mm	L
weight of wooden handle of Hacksaw	$wtowhhs$	Independent	kg	M
length of wooden handle of hacksaw	$lowhhs$	Independent	cm	L
Hardness of Hacksaw blade	$hrhsb$	Independent	No.	-
No. of teeth in hacksaw blade	$noths$	Independent	No.	-
weight of hacksaw	$wths$	Independent	kg	M
length of hammer head	$hhl$	Independent	cm	L
dia of hammer head	$hhd$	Independent	cm	L
weight of hammer head	$hwt$	Independent	kg	M
length of wooden handle of hammer	$hwhl$	Independent	cm	L
weight of wooden handle of hammer	$hwhwt$	Independent	kg	M
nail remover length	$nrl$	Independent	cm	L
nail remover width	$nrb$	Independent	cm	L
nail remover thickness	$nrt$	Independent	mm	L
hardness of wooden handle	$hrhw$	Independent	No.	-
hardness of hammer	$hrh$	Independent	No.	-
Wind Speed	$vs$	Independent	meter/seconds	LT-1
Temperature	$T$	Independent	degree centigrade	-
Humidity	$hu$	Independent	%	-
Acceleration due to gravity	$g$	Independent	m/sec <sup>2</sup>	LT-2
length of wooden props	$lopp$	Independent	meter	L
Number of wooden props	$nopp$	Independent	nos.	-
Dia. of wooden props	$diaopp$	Independent	meter	L
weight of wooden props	$wtopp$	Independent	kg	M
hardness of wooden props	$hrppw$	Independent	No.	-

weight of wooden plank	hrplw	Independent	No.	-
Number of wooden plank	nopl	Independent	no.	-
length of wooden plank	lopl	Independent	m	L
width of wooden plank	bopl	Independent	m	L
thickness of wooden plank	thopl	Independent	m	L
weight of wooden plank	wtpl	Independent	kg	M
No. of nails	non	Independent	nos.	-
Hardness of nail	hrn	Independent	No.	-
diameter of nails	don	Independent	m	L
length of nails	ln	Independent	m	L
Initial Pulse Rate Of Worker1	Pi <sub>1</sub>	Dependent	pulse/minute	T -1
Final Pulse Rate Of Worker1	Pf <sub>1</sub>	Dependent	pulse/minute	T -1
Initial Pulse Rate Of Worker2	Pi <sub>2</sub>	Dependent	pulse/minute	T -1
Final Pulse Rate Of Worker2	Pf <sub>2</sub>	Dependent	pulse/minute	T -1
Duration	t	dependent	minutes	T
Extent Of Work done	Af	Dependent	Meter2	L2
Actual area of formwork	Afa	Dependent	Meter2	L2

c) Mathematical approach selected and development of model.:

The mathematical relation between inputs and outputs could be of any form may be polynomial, exponential or log linear. The Buckingham theorem (S.P. Mishra et. al 2011 (2); Piotr D. Moncari et. al, 1981) found suitable for developing the model. As it states that if the inputs and outputs represented in dimensionless pie terms by dimensional analysis then they can be represented by eqn. (1)

$$Y = k \times A^a \times B^b \times C^c \times D^d \times E^e \dots\dots (1)$$

Moreover, the controls over the variables are not affected.

**Combining of variables in pie terms:** The obtained independent variables can be utilized only after modifying or converting into standard dimensionless form. The various dimensions recorded in Table were converted into desired form i.e. the dimensionless pie terms.

**Pie terms:**

**Table 2: Combining of independent variables in Pie terms**

Pie Terms	Dimensionless equations
$\pi_1$	$\frac{A_2 \times W_2 \times Ag_2 \times ht_2}{A_1 \times W_1 \times Ag_1 \times ht_1}$
$\pi_2$	$\frac{hhl \times hhd \times hwhl \times wthh \times wtowh \times nrl \times nrt}{lhs \times avwhs \times lowhhs \times thob \times wths \times wtw h \times nr b}$
$\pi_3$	$\frac{vs \times Hu}{g \times t \times 60}$
$\pi_4$	$\frac{hrhsb \times hrh \times hrhw}{hrn \times hrplw \times hrppw}$
$\pi_5$	<b>Noths</b>
$\pi_6$	$\frac{lopp \times lopl \times lon \times thopl \times wtopp}{dopp \times dopl \times bopl \times diaon \times wtpl}$

**Table 3: Combining Independent Pie Terms:** Above pie terms were further reduced in following A, B, C, D and E dimensionless pie terms -

A	Workers pie term	$\pi_1$	$\frac{A_2 \times W_2 \times Ag_2 \times ht_2}{A_1 \times W_1 \times Ag_1 \times ht_1}$
B	Environmental pie term	$\pi_3$	$\frac{vs \times Hu}{g \times t \times 60}$

C	Tools pie term	$\pi_2 \times \pi_5$	$\frac{hhl \times hhd \times hwhl \times wthh \times wtowh \times nrl \times nrt \times Noths}{lhs \times avwhs \times lowhhs \times thob \times wths \times wtwh \times nrb}$
D	Work station pie term	$\pi_6$	$\frac{lopp \times lopl \times lon \times thopl \times wtopp}{dopp \times dopl \times bopl \times diaon \times wtpl}$
E	Materials pie term	$\pi_4$	$\frac{hrhsb \times hrh \times hrhw}{hrn \times hrplw \times hrppw}$

**Table 4: Conversion of output data:** Similarly the Dependent variables into  $Y_1$ ,  $Y_2$  and  $Y_3$  Pie Terms -

Extent of Work done Pie Term	$Y_1$	$\frac{Af}{lhs \times hhl}$
Human Energy Pie Term	$Y_2$	$\left[ \frac{(Pf_1 + Pf_2)}{2} - \frac{(Pi_1 + Pi_2)}{2} \right] \times t$
Performance Error (% Error in work done)	$Y_3$	$\frac{Afa - Af}{Af} \times 100$

A, B, C, D, E are the final independent pie terms representing workers data, environmental data, tools data, workstation data and materials data and the response variable Y can be stated for all  $Y_1, Y_2$  and  $Y_3$ .

This dimensionless statement (1), transformed into linear relationship using log operation. The log linear relationship so obtained is easy to understand and does not damage any facets of original relationship.

For determining the indices of the relation between output and inputs, we use multiple regressions and Matlab software, thus the models for  $Y_1, Y_2$  &  $Y_3$  obtained as under.

$$Y_1 = 1.057547A^{-0.0259} .B^{-1.0456} .C^{0.0815} .D^{-0.4836} .E^{0.0047} \dots (2)$$

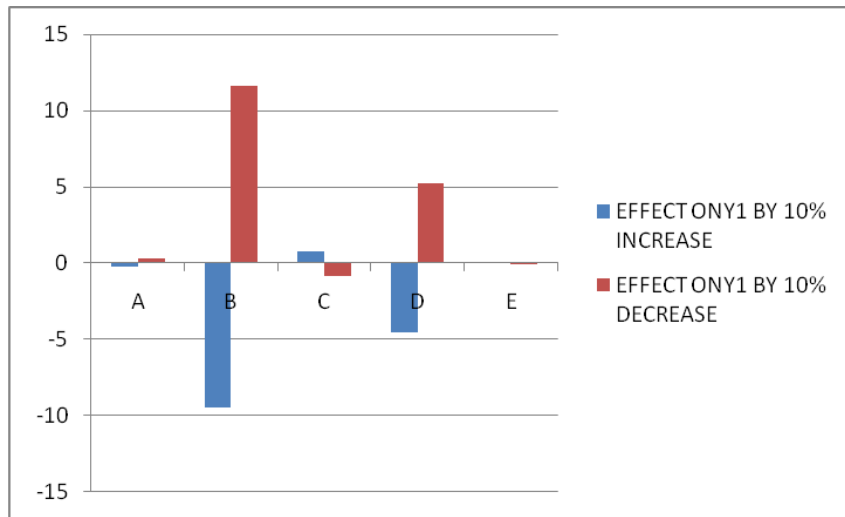
$$Y_2 = 1.000023A^{0.0066} .B^{-1.1617} .C^{0.3225} .D^{-0.455} .E^{0.0017} \dots (3)$$

$$Y_3 = 1.000011A^{0.436} .B^{0.1844} .C^{0.0394} .D^{0.383} .E^{0.0024} \dots (4)$$

### 3. Results and analysis

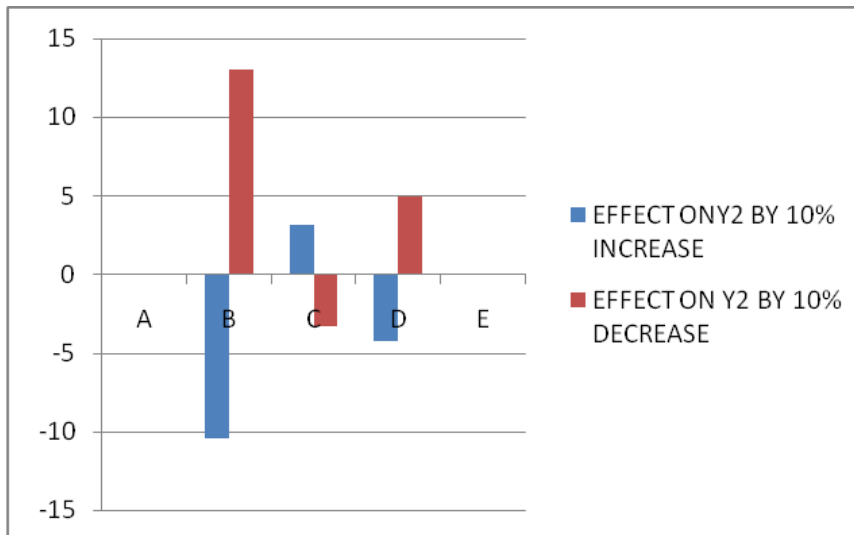
**Interpretation of models:** The numeral multiple of the equations represents the extraneous variables of the models. The indices to A, B, C, D and E in the equations represents relative waitage to affect the output variables. They represents a group of input variables as listed in Table 3 workers data, environmental data, tools data and work station data respectively.

**Sensitivity analysis:** when a model has multiple input parameters then it becomes important to know for a certain value of positive and negative variation which parameter is influencing maximum and output parameter is sensitive up to what extent. To check the sensitivity of each model the set of output and input parameters are selected in which has minimum error in from Y observed. Sensitivity of a model is the percentage influence on Y, by 10% positive or negative variations keeping the other variable to its minimum error set.



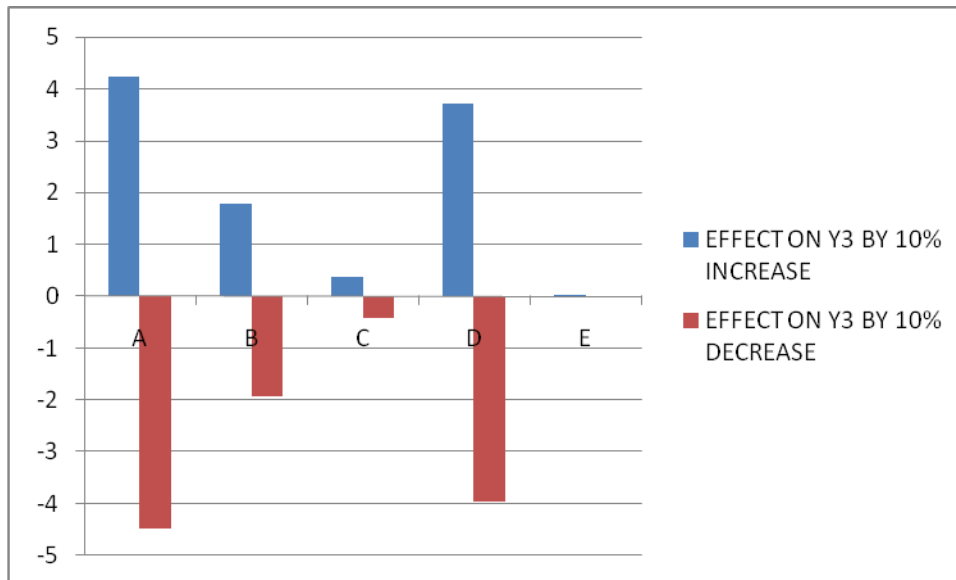
**Fig. 2: Influence of individual input variable in % of Y<sub>1</sub>**

Figure 2 shows the comparative degree of influence by input variables in percentage on Y<sub>1</sub> (Extent of work done). The figure represents that environmental data(B) and work station data(D) has significant influence but B is most influencing but effect is inversely proportional to variations. Extent by which it influences Y<sub>1</sub> i.e. productivity indicated by the graph.



**Fig. 3: Influence of individual input variable in % of Y<sub>2</sub>**

Figure 3 shows the influence of variations in inputs on Y<sub>2</sub>, which represents the Human energy consumption. The above figures imply that the input variable A is most influential and C is least influential. The A indicates the ratio of workers data i.e.,  $\frac{W_2}{W_1}$  and as A is influencing inversely, by positive increment in A the Y<sub>2</sub> is reducing, so to reduce the Y<sub>2</sub> worker 2 should be so selected that its anthropometric data be higher than worker 1.



**Fig. 4: Influence of individual input variable in % of Y3**

Figure 4 shows the degree of influence by individual input variables on  $Y_3$  Performance Error. The above figure clearly indicate that input variables A and D are highly influential to  $Y_3$ , so to reduce the  $Y_3$  we should reduce A and D.

**Optimization of the models:** Having known the form of mathematical model it is the need to optimize the models. Since in this study the no. of variables are more than one for optimization analysis using MS Excel Solver multivariate constrained optimization is performed. The Ms Excel solver tools used generalized reduced gradient concept for optimization. Under the following constraints situation:

**Table 5: Constraints for Multivariate optimization**

Input terms	max	min
A	2.07	0.68
B	0.01	0.00
C	131.25	19.75
D	179.58	24.65
E	3.29	3.29

The Optimization results found are:

For Maximizing  $Y_1$  Extent of work done, the values of set of inputs A, B, C, D, and E in Eqn. (2) - 0.68, 0.01, 131.25, 24.65 and 3.29, provided maximum productivity pie term i.e.  $Y_1=42.47$ .

For Minimizing  $Y_2$  i.e., Human energy, the set of inputs A, B, C, D, and E in Eqn. (3) should be 0.68, 0.01, 19.75, 179.58 and 3.29, provided minimum human energy  $Y_2=50.60$ .

Similarly, for Minimizing  $Y_3$  Performance Error, the values of A, B, C, D, E in Eqn. (4) should be 0.68, 0.00, 19.75, 24.65 and 3.29, provided minimum performance error  $Y_3=1.20$ .

#### 4. Validation of model using Neural Network

Validation of FDBM models achieved by:

- i) Comparing the ANN simulation results with Field observed (Vahid K. Alilou, 2009; Tapir S.H. et Al, 2005).

ii) By performing Reliability analysis of (S.P. Mishra et al., 2011-1)

**ANN Simulation:** ANN Simulation of the gathered field data using Matlab software have been performed. Which results into simulation based model and quantify appropriate non-linear behaviour of effect (responses) as influenced by causes (Inputs).

**Reliability:** Reliability of the individual model established using the following relation

$$Reliability = 1 - Mean Error$$

$$Mean Error = \frac{\sum(x_i \times f_i)}{\sum(f_i)}$$

$$\therefore Reliability = 1 - \frac{\sum(x_i \times f_i)}{\sum(f_i)}$$

Where

$x_i$  is percentage error expressed in fraction and

$f_i$  frequency of occurrence

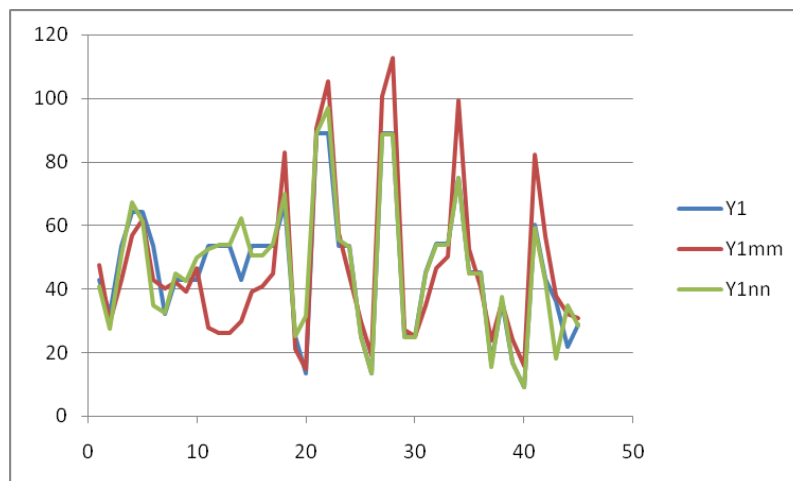
Mean error calculated by obtaining difference between observed values and respective values obtained from mathematical model with respect to observed value. Mathematically

$$Percentage Error = \frac{Observed Value - Mathematical Model Value}{Observed value}$$

**Table 6: Comparison of Reliability calculated for Mathematical Model and ANN prediction**

$Y_{1m}$	$Y_{1nn}$
0.79	0.90
$Y_{2m}$	$Y_{2nn}$
0.76	0.71
$Y_{3m}$	$Y_{3nn}$
0.34	-0.12

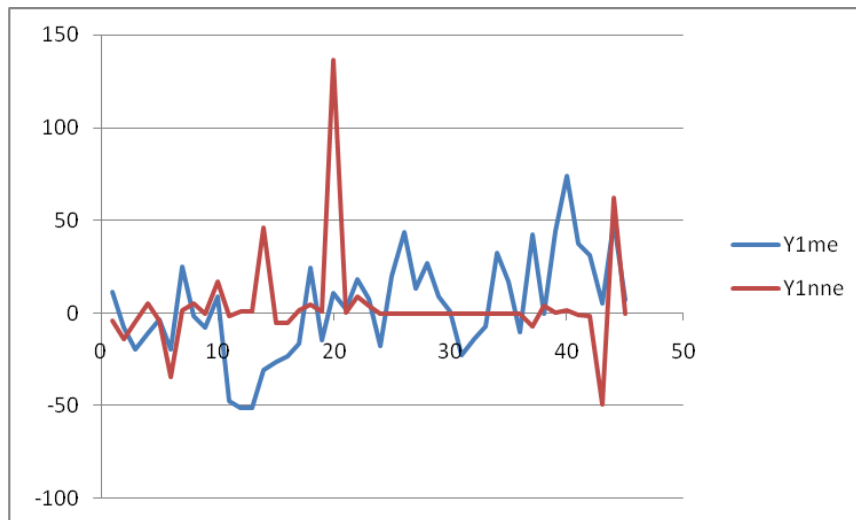
**a. Validation of Productivity model (Y1)**



**Figure 5: Comparative plot of  $Y_1$ ,  $Y_{1cal}$  and  $Y_{1nn}$  (Neural Prediction)**



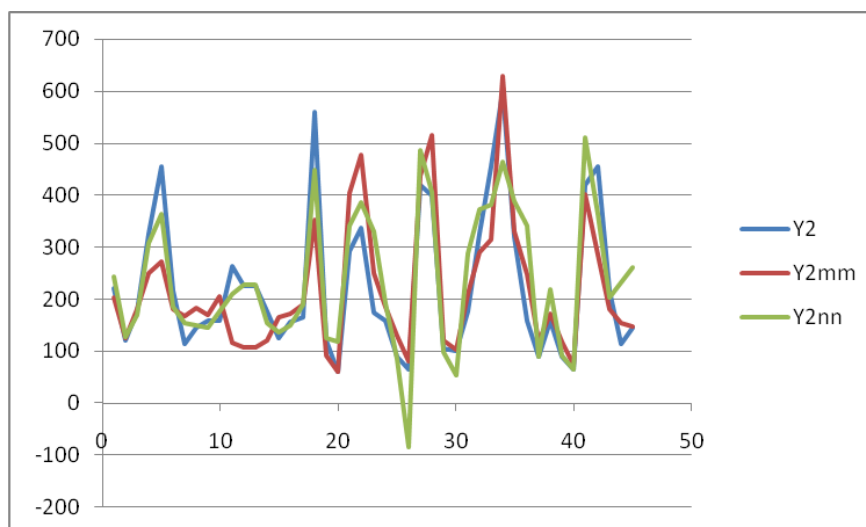
In Figure 5 on ordinates productivity in dimensionless pie terms and on abscissa the number of observations have been plotted which indicates the proximity and variations in observed output  $Y_1$ , model output  $Y_{1cal}$  with ANN predictions  $Y_{1nn}$  thus validates the developed model for Extent of Work Done i.e. Productivity in Manual formwork Operation.



**Figure 6: Comparative plot of Error in results of model and ANN prediction for  $Y_1$**

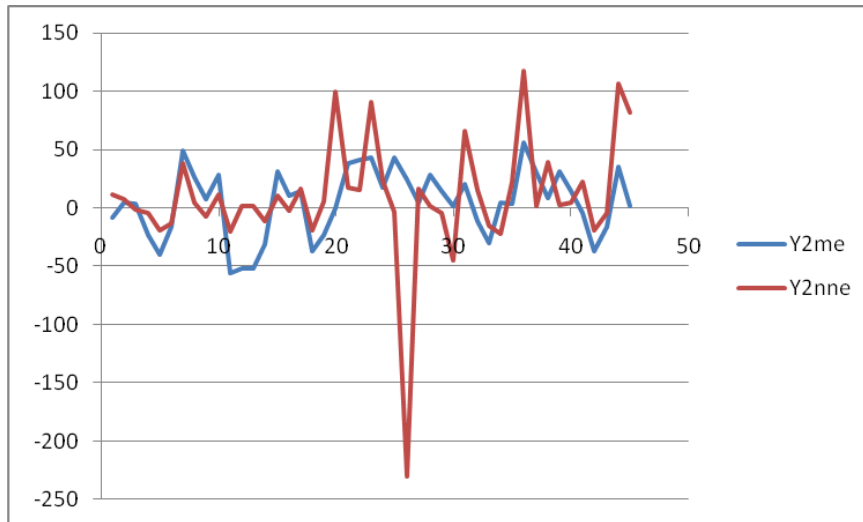
Figure 6 compares the error in  $Y_1$  model results and errors in  $Y_{1nn}$  simulation are distributed. The reliability analysis of mathematical model and neural prediction for  $Y_1$  performed and found 0.79 and 0.90 respectively. Results indicate reliability of mathematical model is quite good and slightly less than neural prediction, thus validate the model.

**b. Validation of Human Energy model ( $Y_2$ )**



**Figure 7 Comparative Plot between observed Human energy ( $Y_2$ ), model output ( $Y_{2m}$ ) and Neural Prediction ( $Y_{2nn}$ )**

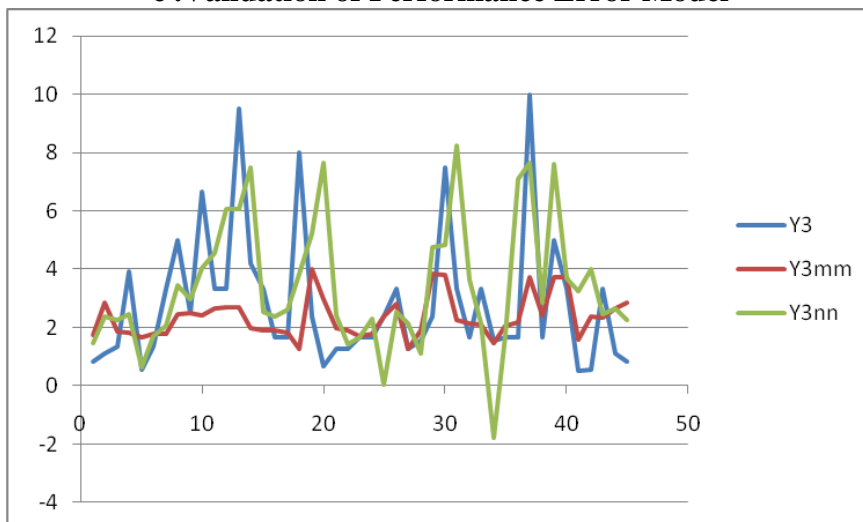
The proximity of observed values of human energy  $Y_2$ , calculated values from mathematical model  $Y_{2cal}$  and neural network simulation results are plotted in Figure 7 which validate the mathematical model.



**Fig. 8: Comparative plot of errors by comparing field data with Y2model and Y2nn**

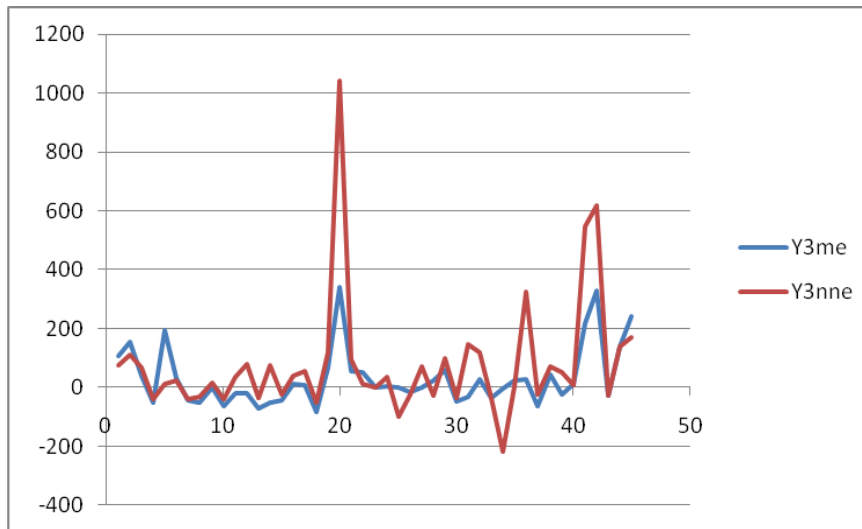
The close proximity of the plot of model error Y2me and simulation error Y2nn is shown in Figure 9. Having calculated the error as shown above, in the next step Reliability of mathematical model and neural predictions performed. The Reliability of Human energy model obtained 0.76 and for ANN model 0.71. Here reliability of model found satisfactory and higher than Validating neural model.

**c .Validation of Performance Error Model**



**Figure 9: Comparative Plot between observed Human Energy (Y<sub>3</sub>), Calculated (Y<sub>3mm</sub>) and Neural Network Prediction (Y<sub>3nn</sub>)**

The Figure 10 shows comparison between the actual fields recorded performance error Y3, Calculate value from model (4) Y3mm and Neural network prediction Y3nn. The graph indicates that Y3mm curve flatter than Y3nn and variations are small so the model Y3 considered as validated.



**Fig. 10: Comparative plot of errors in values of performance error obtained by model  $Y_{3me}$  and neural predictions,  $Y_{3nne}$**

Figure 11 shows the percentage variations in calculated model results and neural network predictions from field observations  $Y_3$ . Though some error are very high and Reliability of  $Y_{3m}$  and  $Y_{3nn}$  obtained 0.34 and -0.12 which may be very low as regard to  $Y_3$  but comparing the trend between  $Y_{3me}$  and  $Y_{3nne}$ , the mathematical model for performance error (4) is validated.

## 5. Discussions

1. The mathematical models obtained from FDBM approach are in polynomial form and complex as each independent major pie terms are multiple of various input parameters as described in Table 3.
2. Interpretation of models gave extent of influence on output of the model by any pie terms or any variables listed in Table 1.
3. By comparing the indices of equation(1), as to maximize the productivity  $Y_1$  the absolute value of indices D found to be most influencing because it is highest whereas the negative sign indicates it should be minimized, further indices of E being positive and second highest it should be maximized. Thus, by analyzing the variables combined in developing D and E major pie terms one can easily suggest the method improvement to get required results.
4. Similarly in equation (2)  $Y_2$  human energy should be minimum, the indices of A, workers data being highest and with negative sign, it is found most influencing and needs to be minimized.
5. In equation (3), the indices of B environmental conditions at work place found to be most influencing and positive so to reduce the error in shearing of rebars minimized.
6. Sensitivity analysis suggest the degree of influence of variables A, B, C, D, E on output  $Y_1, Y_2, Y_3$ . Desired values of the output obtained by adjusting inputs according to this analysis.
7. Optimization analysis suggests the optimum output achieved, if the results of this analysis incorporated in present method of Formwork fixing.
8. ANN simulation validates the model for Productivity, Human Energy and model of Performance Error.
9. Reliability of the FDBM model has been validated by neural prediction.
10. Study of mathematical model output and developed ANN predictions for the phenomenon truly represents the degree of interaction of various independent variables.

## 6. Conclusion and suggestions for future work

1. Field data based modelling concept thus found very useful and can be applied to any complex construction activity as the observations for variables are obtained directly from the work place and include all kind of data such as workers anthropometrics, environmental conditions, tools used and its geometry, layout of work station and materials properties.
2. Modelling and proper analysis can suggest a correct method of doing such activities and modifying the tools geometry, materials for tools with changes in layout of workstation will improve productivity, reduce losses of materials, losses due to error in construction work and ergonomic construction.
- 3 Before finding the sensitivity of inputs, it is necessarily to decide the validity of the models. This is so because though we have taken care to purify the observed data there is a chance of some impure data entering in the mathematical processing of the data.
4. The approach to decide the validity would be to substitute in the model known inputs for every observation & decide the difference in response by model and actually observed response. This will give us pattern of distribution of error & frequency of its occurrence.
5. The formulated models in this study are as per working conditions and environmental conditions of selected building construction sites. This needs to be tested for other working and environmental conditions.
6. It is suggested that the countries where the construction works involves intensive manual works, each activity should be analysed by making FDBM model and a new method of doing work can be developed in various types of construction.
7. The FDBM approach can be applied for Ergonomic construction, mechanization and prioritization in mechanization  
all kind of infrastructure construction as it has been seen that the non availability of construction workers leads to delay the major projects so ergonomic construction is the need of present scenario.

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