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Field Data-Based Mathematical Simulation of Manual Rebar Cutting

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Abstract: Construction process activities are very complex in nature and there have been attempts to simulate them via numerous methods. Manual work, which constitutes a large proportion of total construction in India and developing countries, requires emphasis. Field data-based mathematical simulations develop an empirical relation between inputs and outputs; once the model is developed and weaknesses have been identified, methods can be easily improved and optimised for output goals. This paper covers in detail the process of developing models for the rebar cutting subactivity of reinforced concrete construction in residential buildings. These models are evaluated using sensitivity analysis, optimisation techniques and reliability analysis and are validated using artificial neural networks.

Keywords: FDBM simulation, Developing countries, Rebar cutting, Productivity, Human energy, Performance error

INTRODUCTION

A construction activity (Lucko et al., 2009) appears simple in execution, but there is a complex relationship between inputs and outputs (Schenck, 1961; Suhad et al., 2008; Ahn and Paquet, 2000). The creation of all modern structures features reinforced concrete work as a major activity; concrete has high compressive strength but a low tensile strength; thus, it is reinforced with steel bars commonly known as rebar (Slaughter and Eraso, 1997).

This paper features doctoral work regarding the mathematical simulation of the manual rebar cutting subactivity of reiforced concrete construction (RCC) with the goal of obtaining a generalised mathematical model. All data for the simulation were collected from different construction sites during the execution of the applicable work. The purpose of developing this model was to overcome the deficiencies in current methods, to discover best practices for process improvement and process management and to reduce musculoskeletal injuries and fatigue in the workers.

This approach has been motivated by the principles of construction management and work study in industrial engineering (Ahn and Paquet, 2000; Rwamamara and Holzmann, 2007; Dalela, 1999; Murrel, 1967). When using a mathematical model and a simulation model, they need to be well defined (Maria, 1997).

The terms simulation and model are often used synonymously. However, the distinction between these two terms should be noted.

A model is a product (physical or digital) that represents a system of interest. A model is similar to, but simpler than, the system it represents while

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approximating most of the same salient features of the real system as closely as possible. A good model presents a judicious trade-off between realism and simplicity. A key feature of a model is manipulability. There are physical models, conceptual models, statistical models, mathematical models, business models and so on. Modelling is the act of creating a model of a phenomenon.

Simulation is the process of using a model to study the behaviour and performance of an actual or theoretical system. In a simulation, models can be used to study the existing or proposed characteristics of a system. The purpose of a simulation is to study the characteristics of a real-life or fictional system by manipulating variables that cannot be controlled in a real system. Simulations allow for the evaluation of a model to optimise system performance or to make predictions about a real system. Simulations are useful for studying the properties of a model of a real-life system that would otherwise be too complex, too large/small, too fast/slow, not accessible, too dangerous or unacceptable to engage. While a model aims to be true to the system it represents, a simulation can use a model to explore states that would not be possible in the original system. Simulating is the act of using a model for a simulation.

In this research, the mathematical models are developed using field-based data and contemporary mathematical tools.

The research design includes the following steps:

1. Formulation of the Field Data Based Mathematical Simulation (FDBM) model
   a. Study of the present method of manual rebar cutting
   b. Identification of causes and responses
   c. Decision on observation table format, instruments for measurements and method of measurement
   d. Selection of a suitable mathematical approach for the development of the model
2. Results and analysis
3. Validation of the model through Artificial Neural Network (ANN)

FORMULATION OF FDBM MODEL

Study of the Present Method

Rod cutting work consists of removing bundles of bars of a required size from a stack, straightening them and bringing them to the work station and marking the rods with chalk based on measurements from the design and bar cutting schedule.

The layout of the work station is shown in Figure 1. Operator M_1 holds the bundle of rods with one hand and the chisel handle with the other hand; he must resist the impact of the hammer on the chisel and his legs are considerably bent (Lin and Wang, 2007) around the knee (the weakness of this posture).

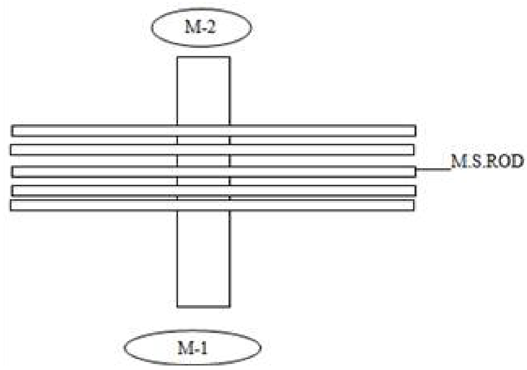

Figure 1. Layout of Work Station

Identification of Causes and Responses: Causes or Inputs to the Activity

The causes, or inputs (Schenck, 1961) have been grouped into five major categories:

1. Workers data: These include static anthropometric data (Eastman Kodak Co., 1983) (specific body segments), height, weight and age of each worker, which vary from site-to-site.
2. Environmental data: The temperature, relative humidity, wind velocity and acceleration due to gravity collected and recorded for each set of observations.
3. Tools data: The tools used for rebar cutting were found to be traditional and not designed according to the workers' anthropometry. The tools commonly used were a hammer with wooden handle and a chisel with a handle; the geometric dimensions of each have been recorded appropriately.
4. Work Station data: These data include the height of the seat of worker 1, height of the anvil, height of hammer dropped by worker M_2 and their relative positions from the anvil center.
5. Materials data: These data include material properties, such as the hardness of rebar, the hardness of the hammer and chisel and the hardnesses of their handles, which affect the performance of the work.

Response data

In performing the rebar cutting subactivity, the responses of this operation considered for study are as follows: (Y_1) Extent of work done, (Y_2) Human energy consumed and (Y_3) Percentage performance error in shearing of the rebar.

Extraneous variables

The variables that affect the responses are difficult to measure or identify. These variables include vibrations generated in the anvil by the hammer, motivation of the workers and the type of organisational setup.

Decision on Observation Table Format, Instruments for Measurements and Method of Measurement

A suitable observation table was designed to record all of the data systematically.

Table 1. Observation Table of Mild Steel (MS) Rods Cutting Operation based on Independent Variables (Causes)

Workers Data	Environmental Data	Tools Data	Work Station Data	Materials Data
Anthropometric data, height, weight, age	Ambient temperature, humidity, wind velocity, acceleration due to gravity	Geometries, weights, material properties of the tools	Distance, height of anvil, height of workers seat	Hardness, shear strength

Table 2. Observation Table of MS Rods Cutting Operation based on Dependent Variables

Time Taken For Activity	Extent of Work Done	Human Energy	Error in Work Executed
minute	kg	Pulse/minute	%

Selecting a Suitable Mathematical Approach for Development of Model

The mathematical relationship between inputs and outputs could be of any form, be it polynomial, exponential or log linear. The Buckingham theorem (Mishra, Parbat and Modak, 2011b; Moncari et al., 1981) is suitable for developing the model because it states that if the inputs and outputs can be represented as dimensionless pi terms by dimensional analysis, then they can be represented by their product and the indices can be obtained by multiple regressions and the control over the variables is not affected. The variables are listed in the table with their symbols, units and dimensional equation.

Table 3. Name of Variables, Symbols and Dimensional Equation of Input Variables

Name of Variables	**Symbols**	**Unit of Measurement**	**Dimensional Formula**
Anthropometric data of worker 1	A_1	cm	L
Weight of worker 1	W_1	kg	M
Age of worker 1	Ag_1	Years	–
Height of worker 1	Ht_1	cm	L
Anthropometric data of worker 2	A_2	cm	L
Weight of worker 2	W_2	kg	M
Age of worker 2	Ag_2	Years	–
Height of worker 2	ht_2	cm	L
Wind speed	vs	meters/second	LT^{-1}
Humidity in percentage	hu	%	–
Acceleration due to gravity	g	meters/second2	LT–2
Time	t	minute	T
Wt of head of hammer	W_h	kg	M
Wt of wooden handle	W_{wh}	kg	M
Length of hammer head	H_l	cm	L
Diameter of hammer handle	d_2	cm	L
Length of chisel	*lc*	cm	L
Length of chisel handle	l_{ch}	cm	L
Diameter of chisel handle	D_1	cm	L
Angle of chisel tip	a	Angle in degrees	–
Seat height of worker 1	S_2	cm	L
Distance of worker 2 from anvil centre	X_2	cm	L
Height of anvil	S_1	cm	L
Distance of worker 1 from anvil centre	X_1	cm	L
Height of hammer drop	Hd	cm	L
Diameter of bar	Ø	cm	L
Hardness of hammer	H_{roh}	no.	–
Hardness of chisel	H_{roc}	no.	–
Hardness of hammer handle wood	H_{row}	no.	–
Number of rods at a time	N	no.	–
Modulus of elasticity of rebar	E	kg/cm2	ML–2
Strength of rebar in shear	S_{sh}	kg/cm2	ML–2

Combining of variables

The obtained independent variables were converted into dimensionless pi terms in Table 4 and arranged by observations in the dimensionless pi terms.

Table 4. Combining of Independent Variables in Pi Terms

Pi Terms	Variables
π_1	$\frac{A_2 \times W_2 \times Ag_2 \times ht_2}{A_1 \times W_1 \times Ag_1 \times ht_1}$
π_2	$\frac{W_h}{W_{wh}}$
π_3	$\frac{h_1 \times W_h \times d_2 \times l_{hh}}{l_c \times W_c \times d_1 \times l_{ch}}$
π_4	$\frac{v_s \times h_u}{g \times t \times 60}$
π_5	$\frac{H_{roh} \times H_{roc}}{H_{ror} \times H_{row}}$
π_6	$\frac{H_d}{\phi}$
π_7	$\frac{S_2 \times X_2}{S_1 \times X_1}$
π_8	n
π_9	a
π_{10}	$\frac{E}{S_{sh}}$

Table 4 shows the combination of the field data using dimensional analysis; thus, each pi term is a dimensionless quantity.

Combining pi terms: Derived from Table 4

To make dimensionless terms by observing their dimensions,

A = Workers pi 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 pi term = $\pi_4 = \frac{vs \times hu}{g \times t \times 60}$

C = Tools pi term = $\pi_2 \times \pi_3 \times \pi_9 = \frac{Wh}{Wwh} \times \frac{h_1 \times Wh \times d_2 \times lhh}{lc \times Wc \times d_1 \times lch} \times \alpha$

D = Works Station pi term = $\pi_6 \times \pi_7 = \frac{S_2 \times X_2}{S_1 \times X_1} \times \frac{H_d}{\phi}$

E = Materials Pi Term = $\pi_5 \times \pi_8 \times \pi_{10} = \frac{H_{roh} \times H_{roc}}{H_{ror} \times H_{row}} \times n \times \frac{E}{S_{sh}}$

Conversion of dependent variables into pi terms: Extent of work done,

$P = C_S \times n$

$$Y_1 = \frac{P}{d_1 \times d_2}$$

Human energy pi term: Human energy measured in average pulse rate increase (Murrel, 1967),

$$Y_2 = \left[\frac{(Pf_1 + Pf_2)}{2} - \frac{(Pi_1 + Pi_2)}{2} \right] + t$$

Y_3 = Performance Error in %

$$Y_3 = \frac{(l - l') \times 100}{l}$$

where l is the required length of rebar to be cut and l' is the actual length found after cutting.

Mapping Buckingham's theorem, the dependent and independent variables can be written in the following form as a homogeneous dimensionless equation:

$$Y_1 = K_1 \times A^{a1} \times B^{b1} \times C^{c1} \times D^{d1} \times E^{e1}$$

where A, B, C, D and E are the independent pi terms that represent workers data, environmental data, tools data, workstation and materials data and the dependent pi terms in terms of Y_1, Y_2 and Y_3, respectively.

To determine the indices of the relationship between outputs and inputs, we use multiple regressions and MATLAB software. Because of the detailed analysis and data involved, the calculation of indices has not been included in this paper.

Thus, the models for (Y_1) extent of work done, (Y_2) human energy consumed and (Y_3) percentage performance error in shearing of the rebars have been formulated as follows:

$$Y_1 = 1.000021A^{-0.06773}.B^{-0.0296}.C^{-0.0581}.D^{-0.9855}.E^{0.7788} \quad \text{Eq.1}$$

$$Y_2 = 0.99995A^{-2.1854}.B^{-0.5900}.C^{-0.5201}.D^{-0.7865}.E^{1.1193} \quad \text{Eq.2}$$

$$Y_3 = 0.999953A^{-0.6384}.B^{-0.9282}.C^{-0.7909}.D^{-0.4727}.E^{0.2851} \quad \text{Eq.3}$$

RESULTS AND ANALYSIS

Using the developed the empirical relationship between inputs and outputs, the sensitivity and optimisation analyses suggest modifying the present method of rebar cutting.

Sensitivity Analysis

To determine the sensitivity of each model, the set of minimum error outputs and corresponding input parameters were selected. Then, by setting the values of the variables to 10% positive and 10% negative, the effects on Y_1, Y_2 and Y_3 were determined, as shown in Figures 2, 3 and 4.

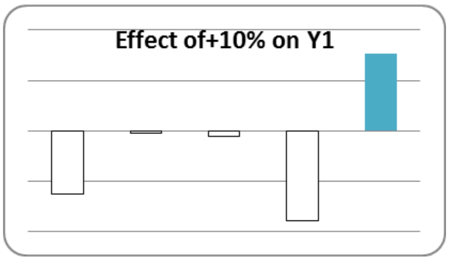

Figure 1(a)

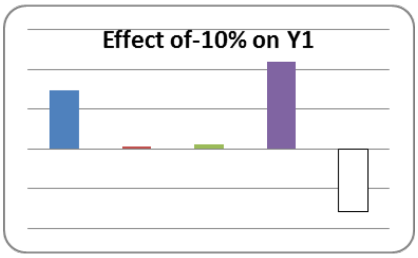

Figure 1(b)

Figures 1(a) and 1(b). Degree of Influence of the Input Variables in Percentage on Y_1

Figures 1(a) and 1(b) show the relative influences of the inputs; some variables have a low influence on Y_1 (productivity of work), the influence of B (environmental data) is maximum and D (workstation data) has minimal effect on Y_1. If one wanted to increase the value of output Y_1, then the values of B and D should be reduced to their minimum values.

The above figure implies that the input variable A is the most influential and that C is the least influential. The variable A reflects the ratio of workers, i.e., $\frac{W_2}{W_1}$ and because A has an inverse effect on Y_2 (that is, a positive increase in A results in a reduction in Y_2), to reduce human energy consumption, worker 2 should be selected such that their anthropometric data are higher than those of worker 1.

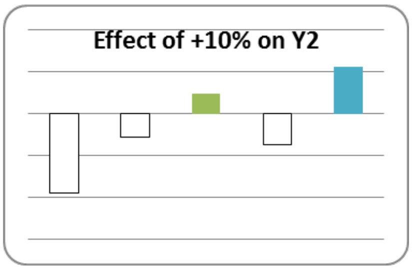

Figure 2(a)

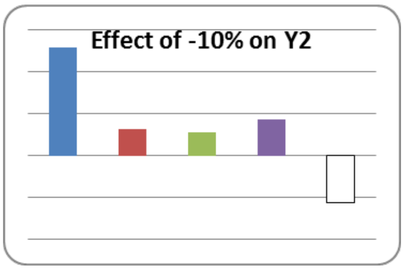

Figure 2(b)

Figures 2(a) and 2(b). Degree of Influence of Individual Input Variables in Percentage on Y_2

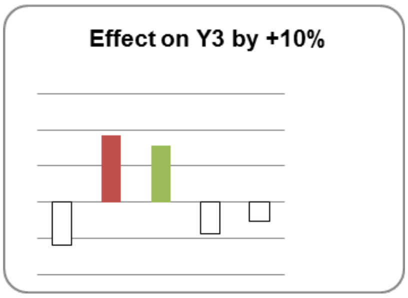

Figure 3(a)

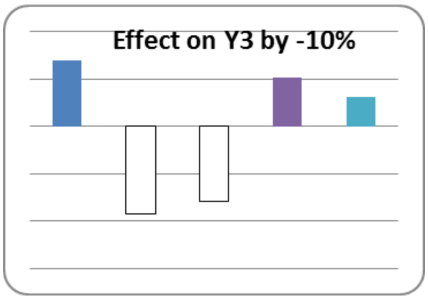

Figure 3(b)

Figure 3(a) and 3(b). Degree of Influence of Individual Input Variables as Percentages on Y_3

The above figure clearly indicates that input variable B is highly influential to Y_3; therefore, to reduce Y_3, we should reduce B, which is a function of wind velocity and humidity. Thus, better quality can be obtained if the work can be performed under favourable environmental conditions.

Model Optimisation

The primary objective of this work is not only to develop the models but also to determine the best set of independent variables that will result in maximisation/minimisation of the objective functions. The models have a non-linear form; hence, they must be converted into a linear form for optimisation purposes. This conversion can be achieved by taking the log of both sides of the model. The linear programming technique is then applied, which is detailed below.

The optimisation is subject to the constraints given in Table: 4, which are the ranges obtained from the results of the field observations.

Table 4. Optimisation Constraints

Variable	Maximum	Minimum
A	1.235156	0.701931
B	0.399724	0.097689
C	2500	599.4932
D	549.5	48.14333
E	4100	2677.751

Multi-variate optimisation provides the values of A, B, C, D and E that correspond to the optimal situation, as described below:

1. For maximising Y_1, i.e., the extent of work done, the set of inputs A, B, C, D and E in Equation 1 should be 0.701, 0.098, 599.493, 48.143 and 4100, respectively.
2. For minimising Y_2, i.e., human energy, the set of inputs A, B, C, D and E in Equation 2 should be 1.23, 0.399, 2500, 549.5 and 2677.751, respectively.
3. For minimising Y_3, i.e., % Error on work done, the set of inputs A, B, C, D and E in Equation 3 should be 1.235156, 0.097689, 599.4932, 549.5 and 4100, respectively.

VALIDATION OF MATHEMATICAL MODELS

The validation of the results was achieved as follows:

1. By comparing the ANN simulation results with the output values observed in the field.
2. By performing a reliability analysis.

Validation of Productivity Model (Y1)

Figure 4 compares the observed field data, the model-derived data and the corresponding neural network values and it shows that the field data and neural predictions exhibit similar trends.

In Figure 4, the ordinate plots productivity (converted into dimensionless pi terms) and the abscissa plots the number of observations; this figure illustrates that the proximity and variations in the observed output Y1 and the model output Y_1cal with the ANN predictions Y_1nn validate the developed model for the extent of work done, i.e., productivity in manual rebar cutting operations.

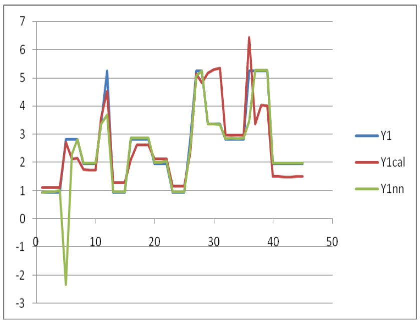

Figure 4. Comparative Plot of Y_1, Y_1cal and Y_1nn (Neural Prediction)

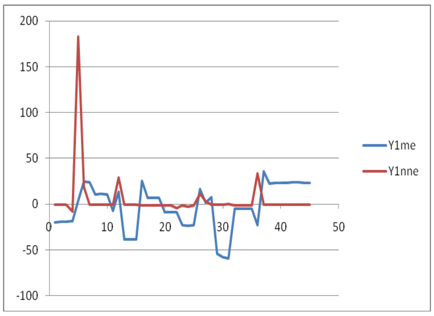

Figure 5. Comparative Plot of Error (%) in the Results of the Mathematical Model and ANN Prediction for Y_1

In Figure 5, the ordinate represents productivity in dimensionless pi terms and the abscissa represents the number of observations; the proximity and variations in observed the output Y_1 and the model output Y1cal with the ANN predictions Y1nn validate the developed model for the extent of work done, i.e., productivity in manual formwork operations.

Validation of Human Energy Model (Y_2)

In Figure 6, the y-axis represents pulse rate increase and the x-axis represents the number of observations; the proximity and variations in the observed values Y_2 and the model output Y_2cal with the ANN predictions Y_2nn validate the developed model for the extent of human energy consumed in manual rebar cutting operations. Figure 6 compares the error in the Y_1 model results and the error in the Y_1nn ANN simulation.

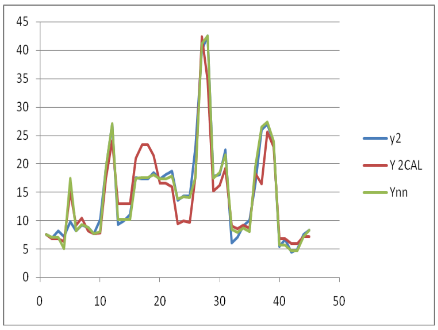

Figure 6. Comparative Plot of Pulse Rate Increase Y_2, Y_2cal and Y_2nn (Neural Prediction)

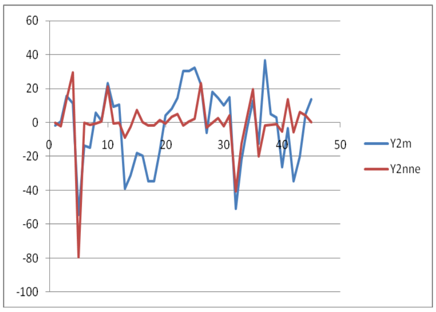

Figure 7. Comparative Plot of Error (%) in the Results of the Mathematical Model and ANN Prediction

Figure 7 plots the error percentage against the number of observations; it indicates productivity errors in the mathematical model Y_2me and the neural prediction Y_2nne corresponding to field observations. The proximity of the observed values of human energy Y_2, the values calculated from the mathematical model Y_2cal and the neural network simulation results are plotted in Figure 7, which validate the mathematical model.

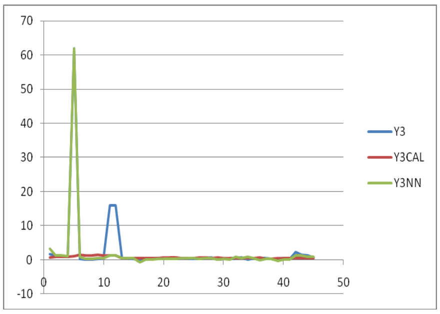

Figure 8. Plot of Y3, Performance Error

Similarly, Figure 8 presents the comparative plot of % error in productivity obtained through construction site data, values calculated using the FDBM model and ANN predictions. The graphs are plotted with % error in rebar cutting operations compared against the number of observations, which shows variations and proximity of the model Y_3.

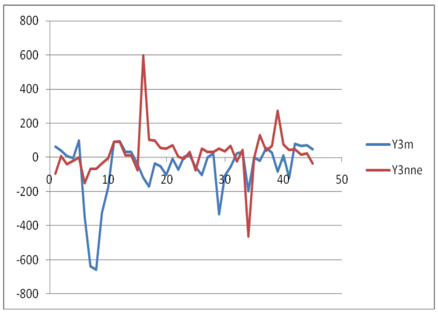

Figure 9. Comparative Plot of Difference in % Error in Work Done Shown By Two FDBM Models: Y_3me and ANN Y_3nne

Figure 9 shows the plot of % error in work done obtained from ANN simulation and mathematical simulation, which indicates the proximity to the variations. The close proximity of the plot of model error Y2me and simulation error Y_2nn is shown in Figure 9.

Reliability

The reliabilities of the individual models were determined 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 *xi* is error and *fi* is frequency of occurrence.

Table 5. Reliabilities of the FDBM Models Compared With the ANN Results

FDBM model		ANN results	
Y1m	0.80	Y11nn	0.93
Y1m	0.82	Y12nn	0.92
Y1m	–0.05	Y13nn	0.24

Table 5 compares the reliabilities of the mathematical models. The results indicate that the reliability of the mathematical model is slightly less than that of the neural prediction, but it is still quite good and validates the model.

DISCUSSION

The following primary statements appear to be justified from the interpretation of the above models:

1. In the previous equations, the first multiple numeral indicates the extraneous variables of the process for respective responses that could not be defined or identified.
2. By comparing the indices of Equation 1 so as to maximise the productivity Y_1, the absolute value of the indices of D was found to be the most influencing because it is highest, whereas the negative sign indicates that it should be minimised. It further indicates that the indices of E should be maximised as they are positive and the second highest. Thus, by analysing the variables combined in developing the D and E major pi terms, one can easily suggest method improvements to obtain the required results.
3. Similarly, in Equation 2, Y_2, human energy, should be minimum. The indices of A, workers data, were the highest and negatively signed and it was found to be the most influencing and in need of minimisation.
4. In Equation 3, the indices of B, environmental conditions of the work place, were found to be the most influencing in regards to minimising the error in the shearing of rebar.
5. The sensitivity analysis revealed the degree of influence of variables A, B, C, D and E on outputs Y_1, Y_2 and Y_3. Desired values of the outputs were obtained by adjusting the inputs according to this analysis.
6. The multi-variate optimisation results can be used for modifying the performance of the activity.
7. The ANN simulations validated the model for productivity, human energy and performance error.
8. The reliability of the FDBM model is found to be satisfactory.

CONCLUSION AND SUGGESTIONS FOR FUTURE WORK

Field data-based modelling concepts were found very useful and can be applied to any complex construction activity because the observations for the variables are obtained directly from the work place. Relevant variables and data include worker anthropometrics, environmental conditions, tools used and their geometry, layout of work stations and material properties. Modelling and proper analysis can suggest a correct method for performing such activities and making changes to tool geometry, tool materials, work station layouts and so on will improve productivity and construction ergonomics and reduce losses of materials and losses due to errors in construction work.

It is suggested that, for countries where the construction work involves intensive manual labour, each component of construction activity should be analysed by creating FDBM models. A new method of performing work can be developed for all types of infrastructure construction; it has been observed that the non-availability of construction workers leads to delays of major projects; therefore, ergonomic construction is in need for the present scenario.

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