Artificial Intelligence Based Model to Predict Labour Productivity for Small & Medium Scale Bus Body Building Society in Present and Post Pandemic Situation

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Abstract

In recession, the lack of potential labour was most important concern for the small and medium scale bus body fabrication industries. In the pandemic covid-19 situation, productivity of these fabrication industries was turndown due to deprivation of labour productivity, postponement of work and cost overshoot which may pilot to argue. In India, Central Tamil Nadu fabrication industries are buttress by immense labour intensity. In this panic situation these industries are struggling to get the better of productivity losses. Diversity of earlier works on detection of the factors with the intention of impact labour productivity in structural industries & manufacturing sectors has been carried out by researches in many countries. Still, those attempts characteristics restricted to credentials and implemented in subjective techniques for analysis in declining bus body fabrication sectors. Ambition of this particular research is to recommend an artificial intelligence based model to predict the "uncertainty factors" influencing labour productivity and safety performance of bus body fabrication industries related to small and medium scale in the pandemic and post pandemic situation.

Key words: Back propagation Neural Network, Uncertainty factors prediction model, bus body fabrication, Productivity & Safety

1 Introduction

Productivity is a key determinant of competitiveness in any engineering organization. The major sources of productivity in an industry are men, machines, materials, money and methods. Agricultural, textile and construction sectors are satisfying the basic human needs. Next to that, vehicle sector is contributing as major role in human mobility also it's participate in economical growth of India. Strong force of these industries are working towards the environmental safety, mean while Indian government initiates schemes to quicker implementation of electric and hybrid vehicles. Bus body sectors are supporting to design and fabrication of high quality passenger vehicles that are creative in fashion & engineering, even as maintaining standards of reliability. In South India, Central Tamil Nadu bus body sectors driven by a squad of young, dedicated and enormous labor work forces. Tran conducted an inclusive examination of construction sector's labour productivity in New Zealand. He declared that there is a link between productivity increases and economic extension [1]. Present research reliable to spot uncertainty factors responsible for deficiency and their probable impact on fabrication of bus body projects. The literature review section defines the labour productivity by different author's perspective and examines the roots of labour productivity and their correlation to legal responsibility. Moreover, the method used by the industry helps to predict the labour productivity (LP). The literature segment assists to give a healthier consideration of the variables influencing productivity.

1.1 Objective

- ✓ Various approaches to define the term Productivity
- ✓ Factor categorization using Drewin's open conversion system
- ✓ Productivity index calculation using normalization of factors
- ✓ Labour productivity prediction using AI technique
- ✓ Put the finger on "uncertainty factors" influencing labour productivity

2 Literature Survey

The term productivity seems to become a buzzword in recent times, so as to discover in several contexts, newspaper, television news, trade magazines, political speeches, consultants advertisements, management briefs, conference proceedings, etc,. Productivity management is vital for long-term endurance of businesses. However, there are serious barrier to obtain successful productivity management because several administrator do not have the proficiency or time to investigate productivity and take required actions in a timely trend.

To simplify the thoughts of this research, the review section can be categorized by three:

- ✓ Put the finger on productivity definition from diverse of research
- ✓ Influencing factor identification and
- ✓ Model Consideration

2.1 Diverse research on productivity definition

Over 1950, official description of productivity defined by Organization in support of European Economic Cooperation as, "Productivity is the proportion obtained by dividing output by one of the factors of input" [2], such that table 1 represents the definition of productivity.

Table 1: Definition of labour productivity

Time Scale	Researches	Definition	Reference
Eighteenth century	Quesnay(1766)	The word productivity appears in article for the first time	[2]
Nineteenth century	Littre(1883)	Faculty to produce	[2]
Twentieth century	Fabricant(1962)	Relationship between output and the means employed to produce this output	[3]
	Sumanth(1984)	The ratio of tangible output to the tangible input	[4]
	ImreBernolak	A family of ratios of output to input	[5]

	(1997)		
Twenty first century	Lingguang Song(2008)	Total factor productivity is ratio between total output to measures the combined input factors of labour, materials, equipment, capital, design	[6]
	Durdyev et.al (2012)	The quantity of work produced per man-hour, equipment-hour, crew-hour worked	[7]
	Farnad Nasirzadeh (2013)	The ratio between completed work and expanded work hours to execute the project.	[8]
	Giorgio Calcagnini (2014)`	Real output per hour worked	[9]
	Ibrahim Halil Gerek (2015)	Ratio of output quantity to quantity of inputs	[10]
	Geert Woltjer	Amount of goods produced within a labour unit	[11]

Bus body fabrication industry as a labour forced engineering concern is a major provider of public mobility product. Productivity is a significant factor in conclude the victory and disappointment of any project. Hence, it can be understand the labour productivity as, "quantitative assessment of the correlation among value of weightage and respondents".

2.2 Influencing factor identification

This research consist efficient evaluation of numerous causes and influencing factors which is affecting LP. The formalized causes of industry poor image [12], Employee's attitude, belief, values & Socio-Psychology [13], Scheduling & Self motivation [14] are predicted by authors and the following table 2 can express different factors and methodology by different author's perspective.

Table 2: Different factors affecting LP and methodology

Industry	**Methodology**	**Optimization**	**Productivity Affecting Factor**	**Productivity Measurement Calculation**	**Reference**
Construction	Dynamic modeling	Labour supply chain	Skilled labor shortage	Not involved	[15]
Manufacturing	FLOPACE Model	Labour productivity	20 factors identified	Weightage index model	[16]
Economics	Bayesian linear model	Capital & labour augmenting	Labour & Capital	Not involved	[17]

		technical change	efficiency		
Manufacturing (Steel rolling mill)	Fuzzy mixed integer bilinear program	Cost minimizing master production schedule	Production plan	Not involved	[18]
Incumbents firms	Regression model	Employment type & time of work	Non-standard work forms & working time	Not involved	[19]
Construction	System dynamics modeling	Labour productivity losses	Endogenous & Exogenous variables	Not involved	[20]
Construction	Panel Ranking	Labour productivity ranking	45 factors analyzed & 6 identified	Importance Index	[21]
Construction	Panel survey ranking using SPSS	Labour productivity	35 factors analyzed by 3 categorize	Relative importance index	[22]
Construction	Artificial Neural Network	Labour productivity	9 factors identified	Importance Index	[23]
Construction	Computational Intelligence	Labour productivity	7 factors identified	Key performance Indicator	[24]
Construction	Artificial Neural Network	Project performance	16 factors identified	Importance Index	[25]
Construction	Artificial Neural Network	Labour productivity	3 factors identified	Importance Index	[26]

The review shows that many researches optimized the labour productivity and identified the productivity affecting factors using importance index calculation methods. Hence, 40 factors were extracted from the survey, which are causes of labour productivity. Among these, influencing factors were examined through critical investigation.

2.3 Model Consideration

Artificial Intelligence (AI) technique has been influential tool of prediction; Different kinds of AI techniques have been utilized in the labour productivity prediction as mention in above table. Even though, LP & uncertainty factors prediction is challenging in this pandemic situation as it requires more effort and quantifying sustainable factors that have an effect on LP in addition to consideration of expression factor interrelationship. The following table 3 can express the description, advantages and

disadvantages of different models. Hence, Back propagation algorithm has been chosen to create prediction model, using of Bayesian regularization & Back propagation for data training for estimated output of rank prediction of "uncertainty factors" and forecasting of labour productivity.

Table 3: Different ANN models

Model	Mathematical Programming Models	Different ANN Models	Back propagation Model(BP)
Description	Linear, Non linear, Integer programming, dynamic programming	GRNN, RBFNN, ANFIS, Elman propagation algorithm	Backward propagation of errors is an algorithm for supervised learning of AI network using gradient descent.
Literature	[15] [17] [18] [20]	[16] [23] [24] [26]	[23] [25]
Advantages	May provide optimal solution	Structure way to search for optimal solution Feed forward method training Hybrid learning algorithm Can solve any function approximation	Robust search algorithm &Efficient way to search for optimal near optimal solution. Multiple hidden layer output Bayesian regularization & Back propagation for data training. Feed forward & Feed backward training.
Disadvantages	Difficult to formulate The gradient-descent in load minimum	One hidden layer output Considerable calculations to evaluate new points& is not able to ignore unrelated Inputs.	Random search is time consuming

3 Methodology

3.1 Flowchart of study

Every research requires model to identify the flow of work and better understanding of execution in a single view. The following figure 1 explains the execution of research for enhanced visibility.

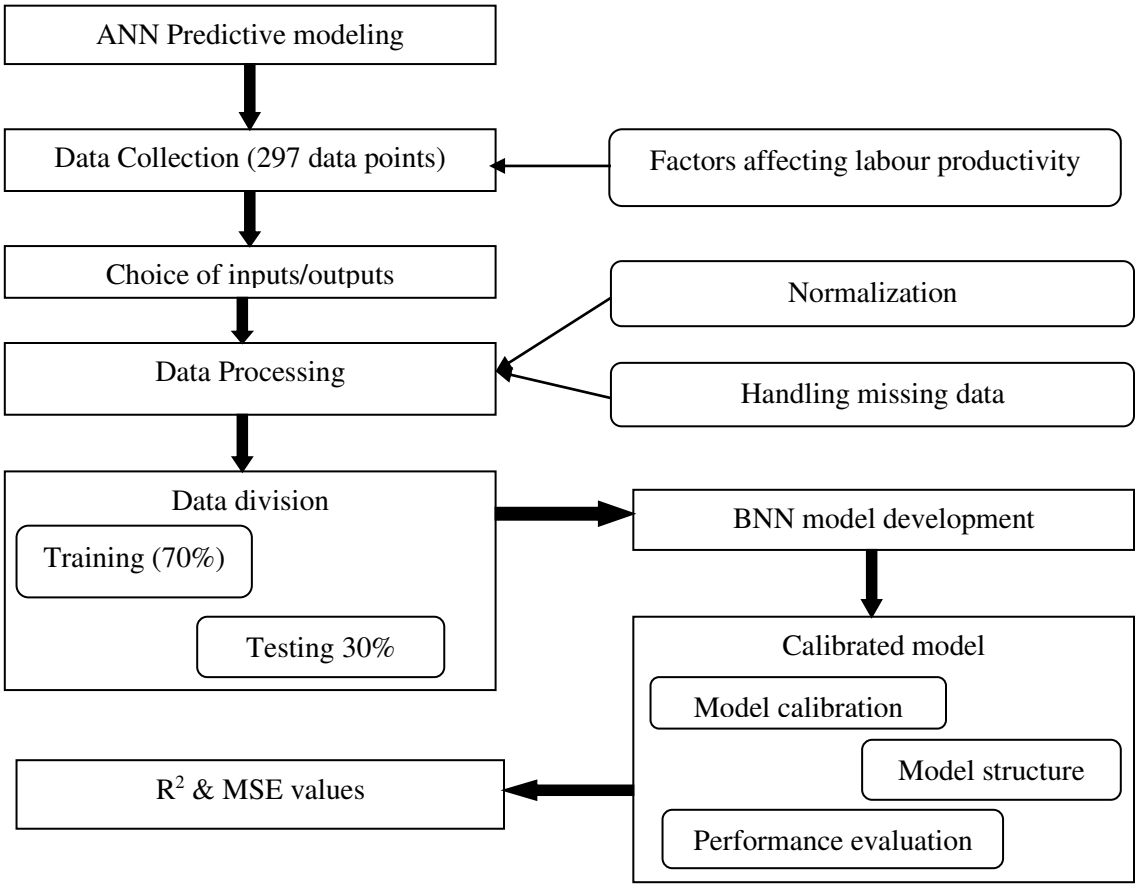

Fig 1: Study flowchart

3.2 Influencing factor identification

Primarily an assessment team was created with experts of 10. In this squad, professional invited from various fields of educational and industry be afford with 40 identified factors which can be extracted from literature and ask over to rate the significance of every factor in come to decision of LP on a level of 1 (May be affect), 2 (Partially affect), 3 (directly affect). In order to facilitate the responses of the panel assessment, 27 informal interrogates were performed with three level of groups. The expert squad identified 16 influencing factor for the further work. Later than the necessary procedure were followed to attain the current research objective of uncertainty factors identification. Through the term “uncertainty factors”, we represent that factor in the lead of such action required to better of productivity.

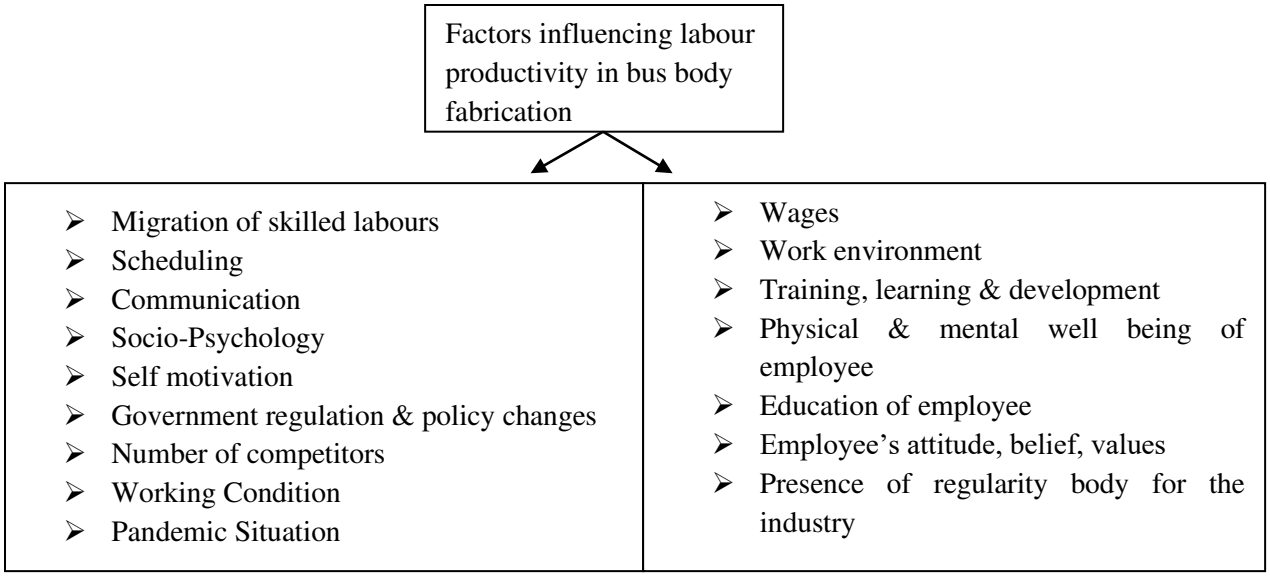

Fig 2: Labour productivity influencing factors

3.3 Theoretical Framework for Factor Categories

Drewin's open conversion system framework is a representation of theoretical structure which demonstrates the correlation between interconnected variables & it will be worn herein the research. It was established based on factors influencing labour productivity in fabrication sector. Figure 3 shows the theoretical frame work for categorization of factors.

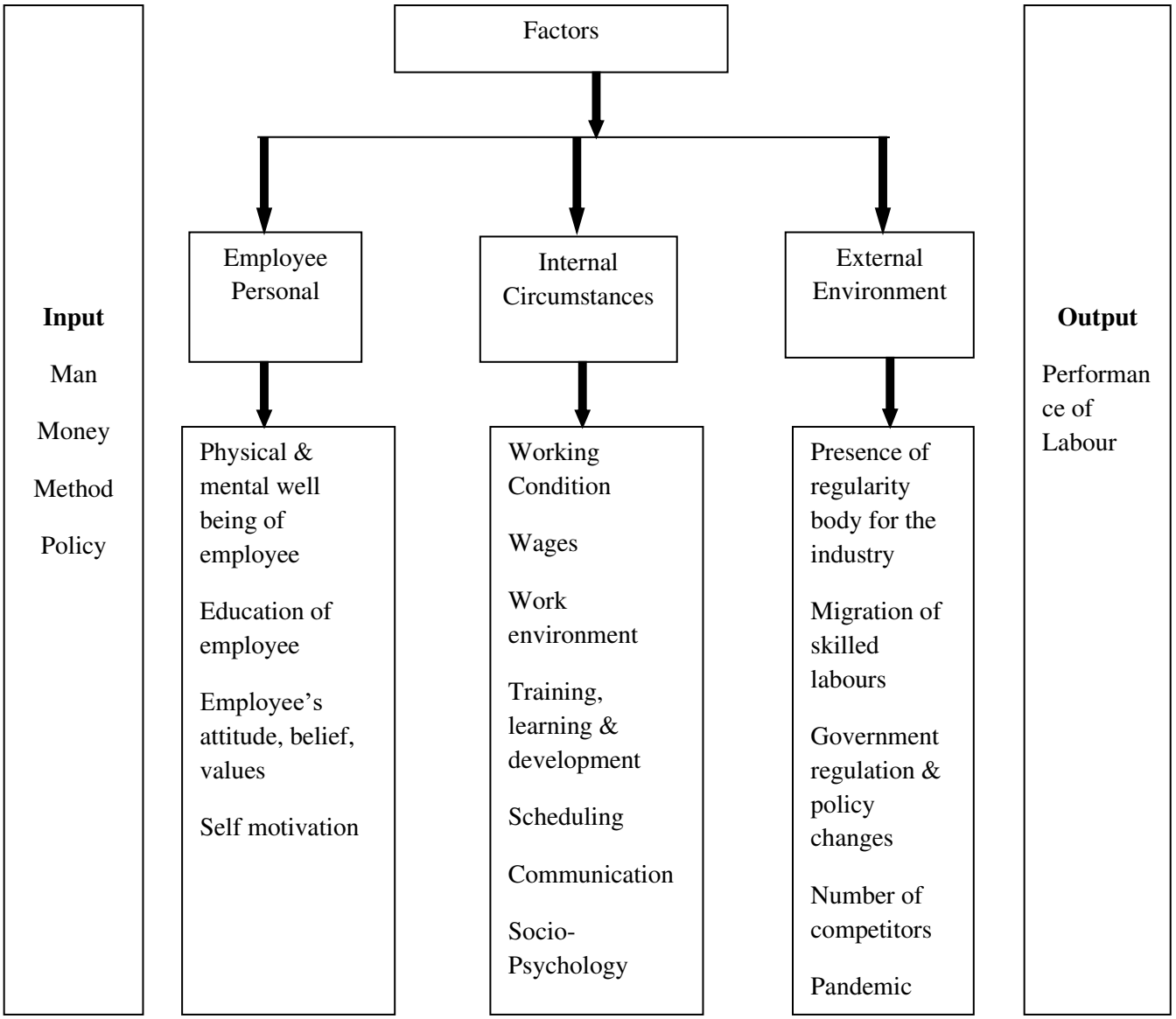

Fig 3: Theoretical Framework *****Source: Drewin's open conversion system

3.4 Productivity Index Calculation

In this research normalized weightage of factor [16] method is used to calculate the productivity index and formulating the datasets.

$$\text{Productivity ndex} = \sum[(\text{Weightage of factor n}) \times (\text{Rating received by factor n})] \quad -----1$$

$$\text{Factor weightage} = \sum\left[\frac{\text{Rating of each expert}}{\text{Maximum rating possible} \times \text{number of experts} \times \text{number of factors}}\right] \quad -----2$$

$$\text{Normalized weightage of factor} = \sum\left[\frac{\text{Weightage of factor}}{\text{Total weightage of all factors}}\right] \quad -----3$$

Factor rating received from respondents =

$$\sum\left[\frac{\text{Rating of each respondent}}{\text{Maximmum rating possible}\times\text{number of respondent}}\right] \quad -----4$$

$$\text{Mean} = \sum\left[\frac{(\text{Sum of all data points})}{\text{Number of data points}}\right] \quad -----5$$

Standard error of sample mean SE $\bar{x}$

$$= \frac{\text{Population of standard deviation } (\sigma)}{\text{Total number of elements}(\sqrt{n})} \quad -----6$$

$$\text{Standard deviaton} = \sqrt{\left[\frac{\sum(x-\bar{x})2}{n-1}\right]} \quad -----7$$

4 Model Development

To predict the uncertainty factor three set of values and twenty seven different combinations were identified using design of experiment and the table 4 shows the descriptive data sets were used for prediction.

Table 4: Descriptive data statistics

Representation	Factors	Mean	Standard Error Mean	Standard deviation	Minimum	Median	Maximum
F1	Education of employee	0.5623	0.0087	0.0452	0.5000	0.5870	0.6000
F2	Employee's attitude, belief, values	0.7577	0.0050	0.0261	0.7330	0.7470	0.7930
F3	Physical & mental well being	0.6667	0.0094	0.0491	0.6200	0.6470	0.7330
F4	Self motivation	0.6977	0.0053	0.0277	0.6670	0.6930	0.7330
F5	Wages	0.7910	0.0025	0.0130	0.7730	0.8000	0.8000
F6	Working Condition	0.7067	0.0022	0.0112	0.6930	0.7070	0.7200
F7	Working Environment	0.6757	0.0012	0.0062	0.6670	0.6800	0.6800
F8	Training & Learning	0.8777	0.0035	0.0179	0.8530	0.8870	0.8930
F9	Scheduling	0.9043	0.0022	0.0117	0.8930	0.9000	0.9200

F10	Communication	0.8287	0.0022	0.0117	0.8130	0.8330	0.8400
F11	Socio-psychology	0.7133	0.0010	0.0054	0.7070	0.7130	0.7200
P1	Productivity	0.7443	0.0015	0.0077	0.7260	0.7440	0.7600

Later on to scrutinize the strength and direction of a linear relationship among database variables Pearson correlation coefficient method were employed. Correlation coefficients lie down in the range of -1 and +1. A superior unconditional coefficient values end results in a healthier association among variables. In this case, it can be shown an exact value of 1 state that an ideal linear relationship & 0 state that nonlinear relationship among variables in Pearson correlation method. The table 5 indicates that the correlation among parameters, the majority of the occasion is an estimated near 0. Accordingly none of the correlates very much and there is no over inference experience.

$$\rho = \frac{(\sum_{i=1}^{n}(\mathrm{x_i} - \bar{\mathrm{x}})(\mathrm{y_i} - \bar{\mathrm{y}}))}{(\mathrm{n}-1)\mathrm{s_x}\mathrm{s_y}} \qquad ------8$$

Table 5: Pearson correlation matrix for input and output parameter

Factors	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	P1
F1	1	-0.002	0.019	-0.021	0.005	-0.015	-0.022	-0.019	-0.017	-0.022	0.016	0.084
F2	-0.002	1	0.041	-0.036	-0.039	0.019	-0.032	0.005	-0.056	-0.02	0.047	0.023
F3	0.019	0.041	1	-0.011	-0.04	0.032	-0.006	0.024	-0.033	0.005	0.026	0.0108
F4	-0.021	-0.036	-0.011	1	0.036	-0.031	0.002	-0.025	0.026	-0.009	-0.02	0.078
F5	0.005	-0.039	-0.04	0.036	1	-0.015	0.033	-0.001	0.054	0.022	-0.045	0.09
F6	-0.015	0.019	0.032	-0.031	-0.015	1	-0.03	-0.011	-0.037	-0.025	0.033	-0.014
F7	-0.022	-0.032	-0.006	0.002	0.033	-0.03	1	-0.025	0.02	-0.011	-0.015	0.037
F8	-0.019	0.005	0.024	-0.025	-0.001	-0.011	-0.025	1	-0.024	-0.024	0.022	0.024
F9	-0.017	-0.056	-0.033	0.026	0.054	-0.037	0.02	-0.024	1	0.004	-0.044	0.977
F10	-0.022	-0.02	0.005	-0.009	0.022	-0.025	-0.011	-0.024	0.004	1	-0.001	0.048
F11	0.016	0.047	0.026	-0.02	-0.045	0.033	-0.015	0.022	-0.044	-0.001	1	-0.023
P1	0.084	0.023	0.0108	0.078	0.09	-0.014	0.037	0.024	0.977	0.048	-0.023	1

4.1 Constructing Back propagation model for labour productivity

In the model constricting segment, BNN was used; it is generally utilized for unknown function approximation. Then ideal interrelation along with input variables and output variables can be determined by training datasets addition to forecast the output for new input variable. Herein the three phases (training, validating, testing) of BNN model scrutinized with 297 data points and randomly divided of

70% & 30% using MATLAB 2016a. Of course number of neurons varied from five to fifty & hidden layers from 1 to 2. Generally Bayesian Regularization algorithm (BR) employed for the data training in noisy and small problems. In the training phase as a revision of network bias & weight the errors can be minimized using BR until the best structure was justified. Next to that, validation sets were estimates network generalization capabilities and in test phase independent network performance index.

The interpretation was evaluated by R-squared & MSE through coding as per the subsequent equations, wherever "t_i" represents target value whereas "o_i" represents output value.

$$R^2 = 1 - \sum_i (t_i - o_i)^2) \,/\, \sum_i (t_i - (1/n) \sum_i t_i)^2 \qquad ------ 9$$

$$MSE = \frac{1}{n} \sum_i (t_i - o_i)^2) \qquad ------ 10$$

Table 6: Performance Indices for models with 1 hidden layer

Performance Indices for models with 1 hidden layer										
Neurons	5	10	15	20	25	30	35	40	45	50
MSE	0.0555	0.012	0.02	0.048	0.022	0.039	0.014	0.025	0.018	0.011
R^2	0.8325	0.899	0.918	0.811	0.909	0.844	0.972	0.841	0.88	0.9
R^2 train	0.81	0.914	0.947	0.749	0.947	0.852	0.88	0.484	0.72	0.958
R^2test	0.707	0.703	0.751	0.66	0.847	0.82	0.849	0.71	0.69	0.778

Statistical analysis of R-squared values fluctuates among zero & one and estimating the sum of variations sandwiched among projected and target values. The performance index of BNN model corresponds to 1 hidden layer represents in table 6, figure 4&5 as well as table 7, figure 6&7 represents values of 2 hidden layers.

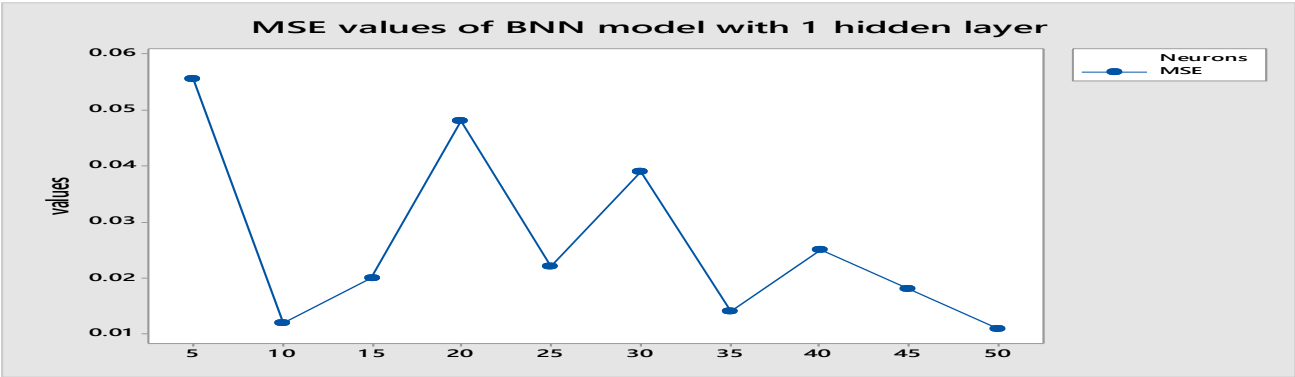

Fig 4: MSE values of BNN model with 1 hidden layer

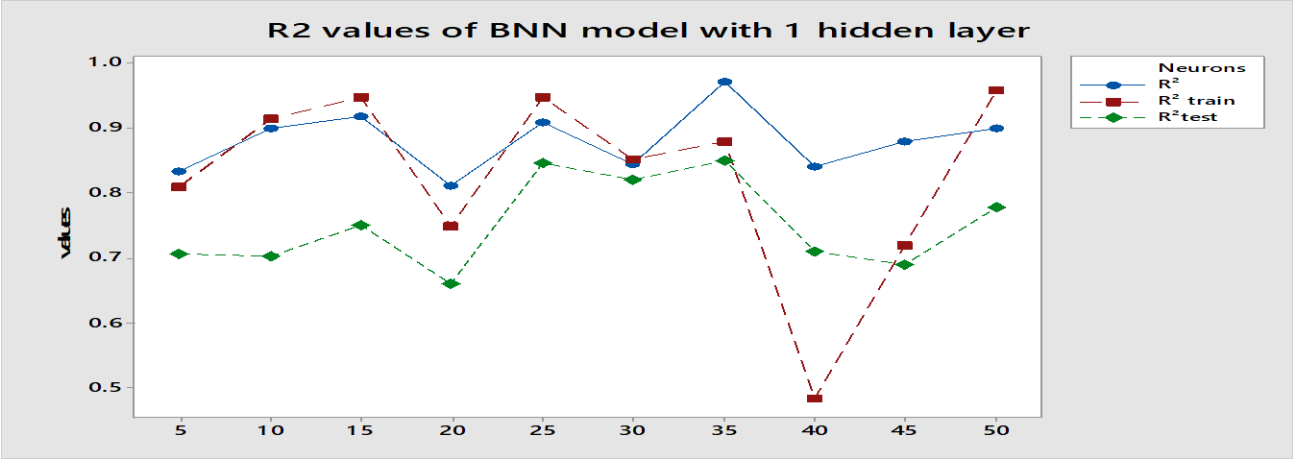

Fig 5: R^2 values of ANN model with 1 hidden layer

Table 7: Performance Indices for models with 2 hidden layers

Performance Indices for models with 2 hidden layer										
Neurons	5	10	15	20	25	30	35	40	45	50
MSE	0.026	0.047	0.00677	0.016	0.022	0.036	0.01	0.017	0.02	0.085
R²	0.761	0.922	0.901	0.875	0.917	0.879	0.817	0.5559	0.901	0.888
R² train	0.785	0.918	0.928	0.908	0.976	0.926	0.955	0.603	0.968	0.888
R²test	0.789	0.7992	0.689	0.889	0.867	0.69	0.76	0.648	0.814	0.649

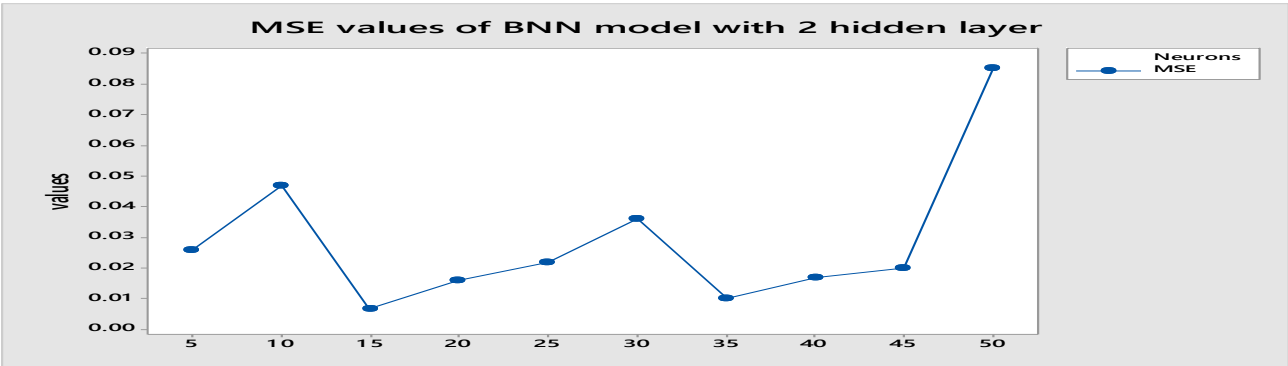

Fig 6: MSE values of ANN model with 2 hidden layers

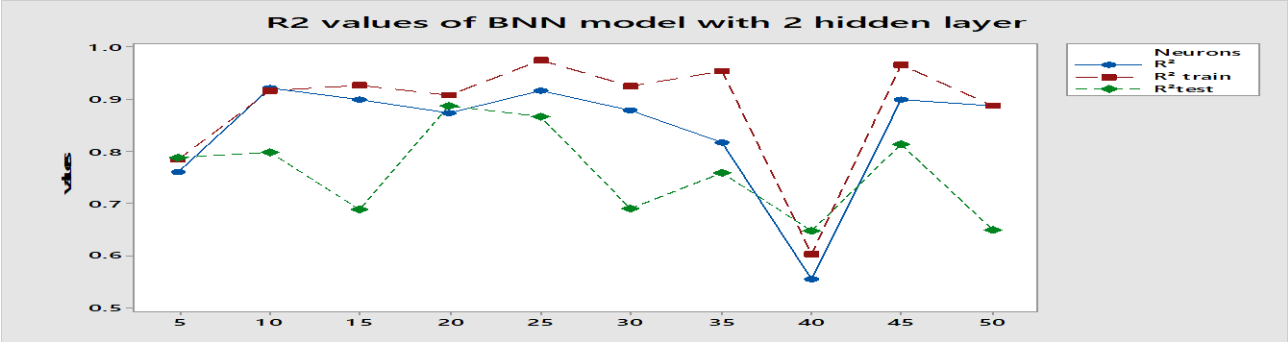

Fig 7: R^2 values of ANN model with 2 hidden layers

4.2 Result & Discussion

Model performance was evaluated by R-squared and Mean Squared Error; summarize in above tables 6&7 for 1&2 hidden layers. It is in clear view; the ultimate model was with two hidden layers and 20 neurons, which illustrate that uppermost accurateness for predicting output results. The model had Mean Squared Error and R-squared performance significance index of 0.016 & 0.889 respectively. The following figure 8 can interpret the relationship of targeted and BNN output values.

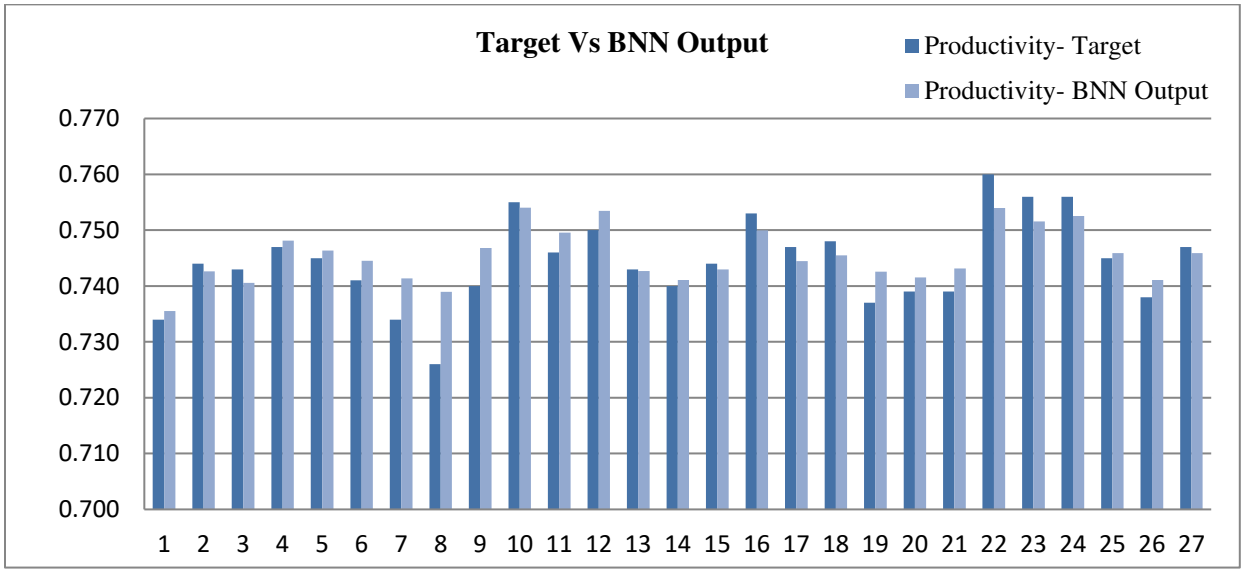

Fig 8: Target and BNN model output interpretation

In prediction perspective, Mean Squared Error was concentrated and noted as 0.016, which is small in error; of course the R-squared in the selected model confirms 0.908 & 0.889 for training and testing dataset. The R-squared in the preferred model be evidence of,

Training fitted line for output =0.66 * Target + 0.25 ------ 11

R-squared value in training dataset is 90.8 % which is signifying that the values of output & target were too close.

Test fitted line for Output = 0.38 * Target + 0.46 ------ 12

The R-squared value of testing was 88.9%, proves that the model is able to predict 89 % of present crisis can resolved by concentrating on “uncertainty factor”. The functional technique is capable to predict the relative importance of variables as shown in figure 9.

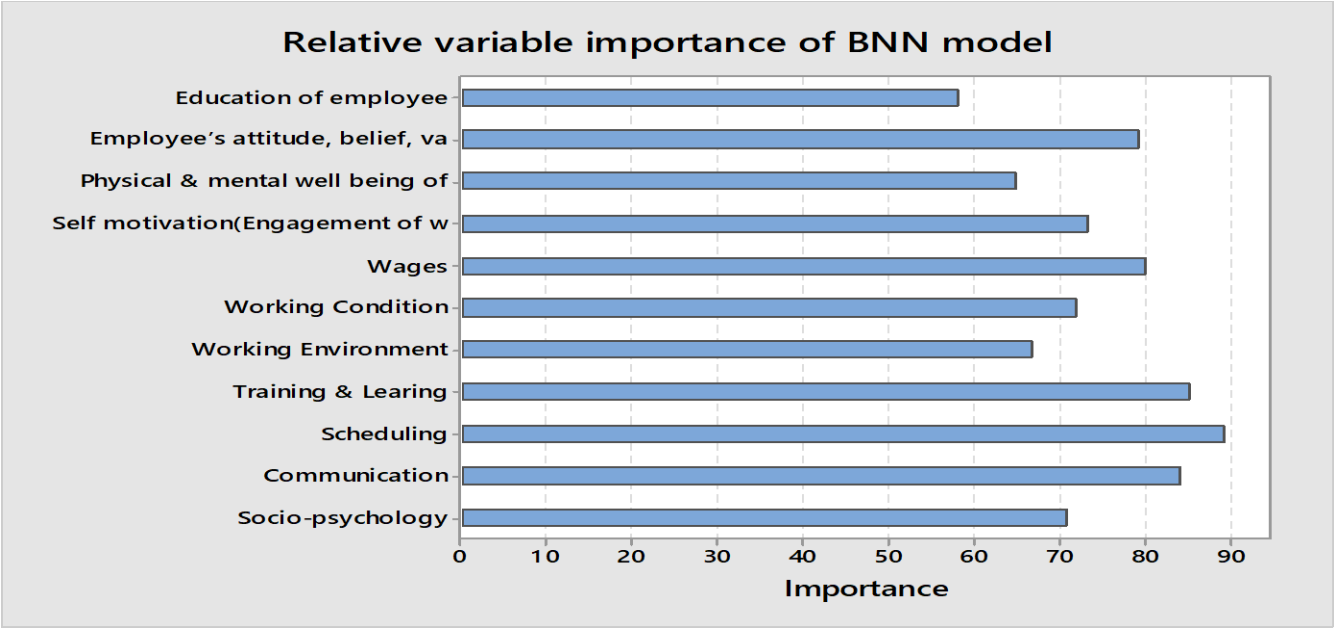

Fig 9: Relative variable importance of BNN model

The interpretation of relative variable importance illustrates that “labour scheduling, training & learning, communication” were symbolized by “uncertainty factor” which leads productivity and safety of labours in this pandemic and post pandemic situations. For the time consumption in implementing stage, first three ranking were considered as “uncertainty factor”.

5 Conclusion

Labour productivity & safety of bus body fabrication segment is an extremely tricky which is buttress by immense labour intensity and an assortment of various factors. Our methodical observation proves this complexity as how “uncertainty factor” affects labour productivity & safety. A fair quantification is a mirror of business situation & be evidence for where it stands towards curial pandemic situation and its competitor. The gap must be identified to make stronger enhancement of productivity. To obtain the fair quantification the executives shall broadcast the significance importance of productivity measurement and enhancement to the owner of the firm and then to entire crew. The owner of the firm must support for the entire quantification executions plan with true spirit and manage that progressing to achieve goals and objectives of the firm. At this point, we would like to highlight the “uncertainty factors prediction model” which enhances the safety, productivity and labor productivity value in pandemic and post pandemic situation. Let the limitation of these studies, that it only includes employee personal and internal circumstance factors and nonappearance of external environment factor.

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Figures

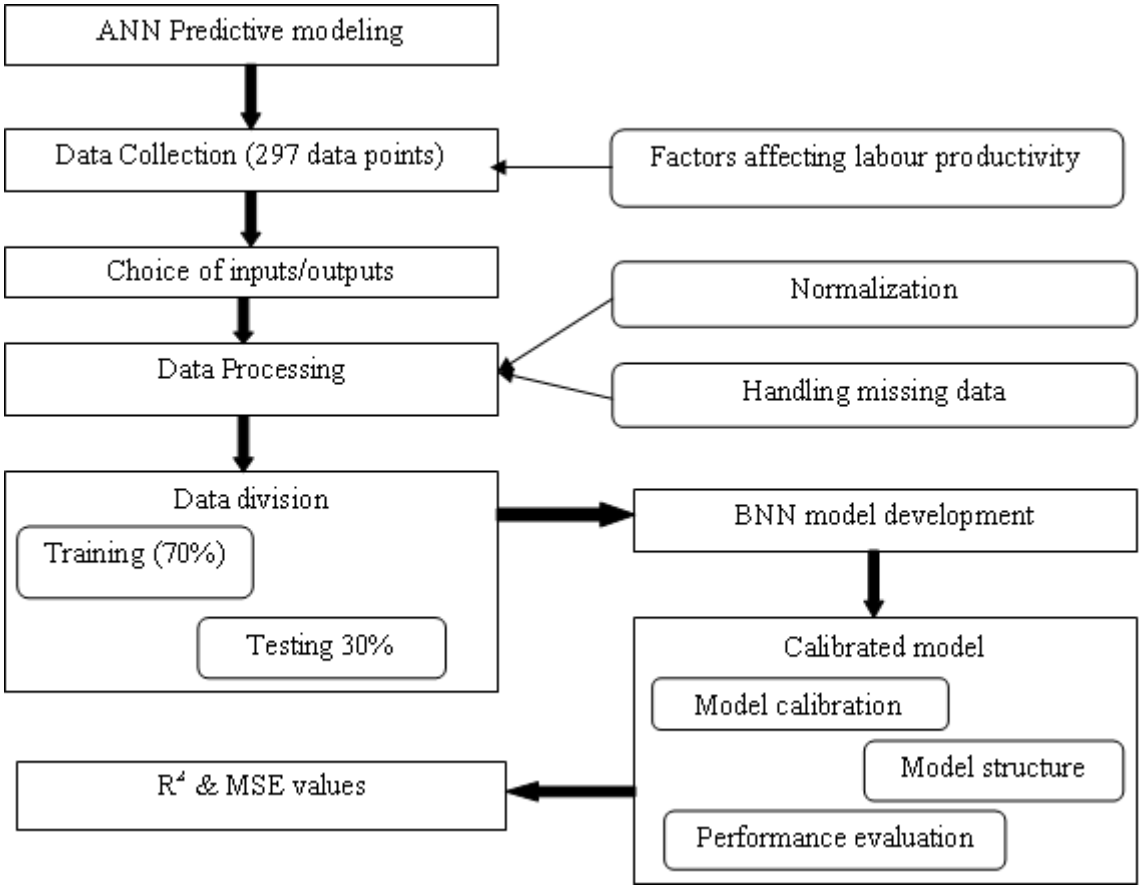

Figure 1

Study flowchart

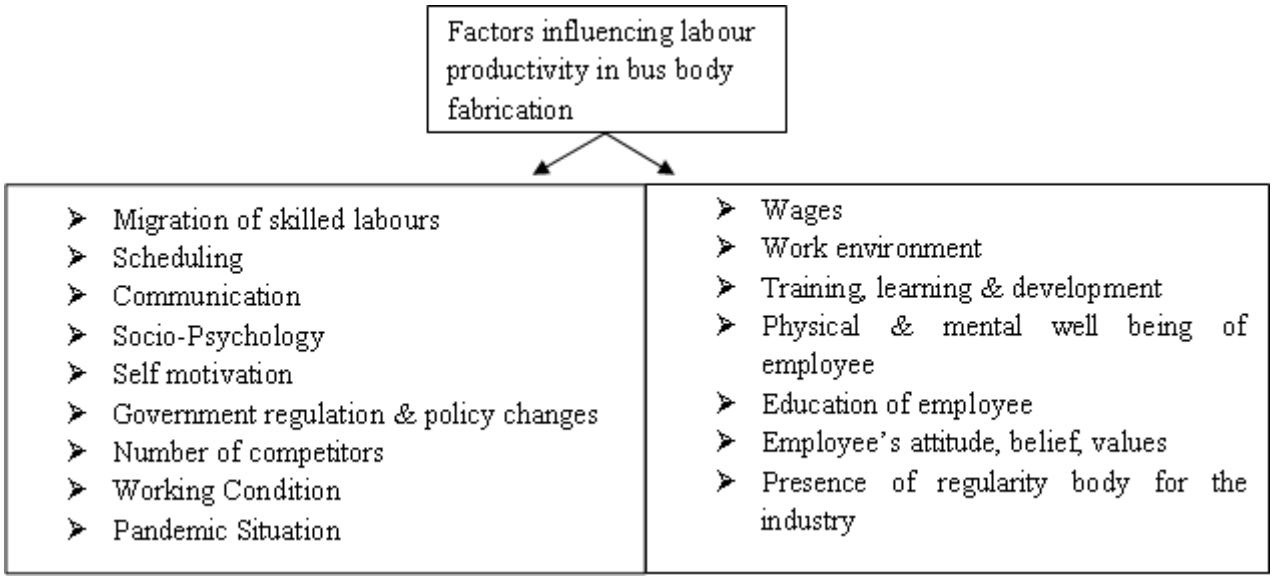

Figure 2

Labour productivity influencing factors

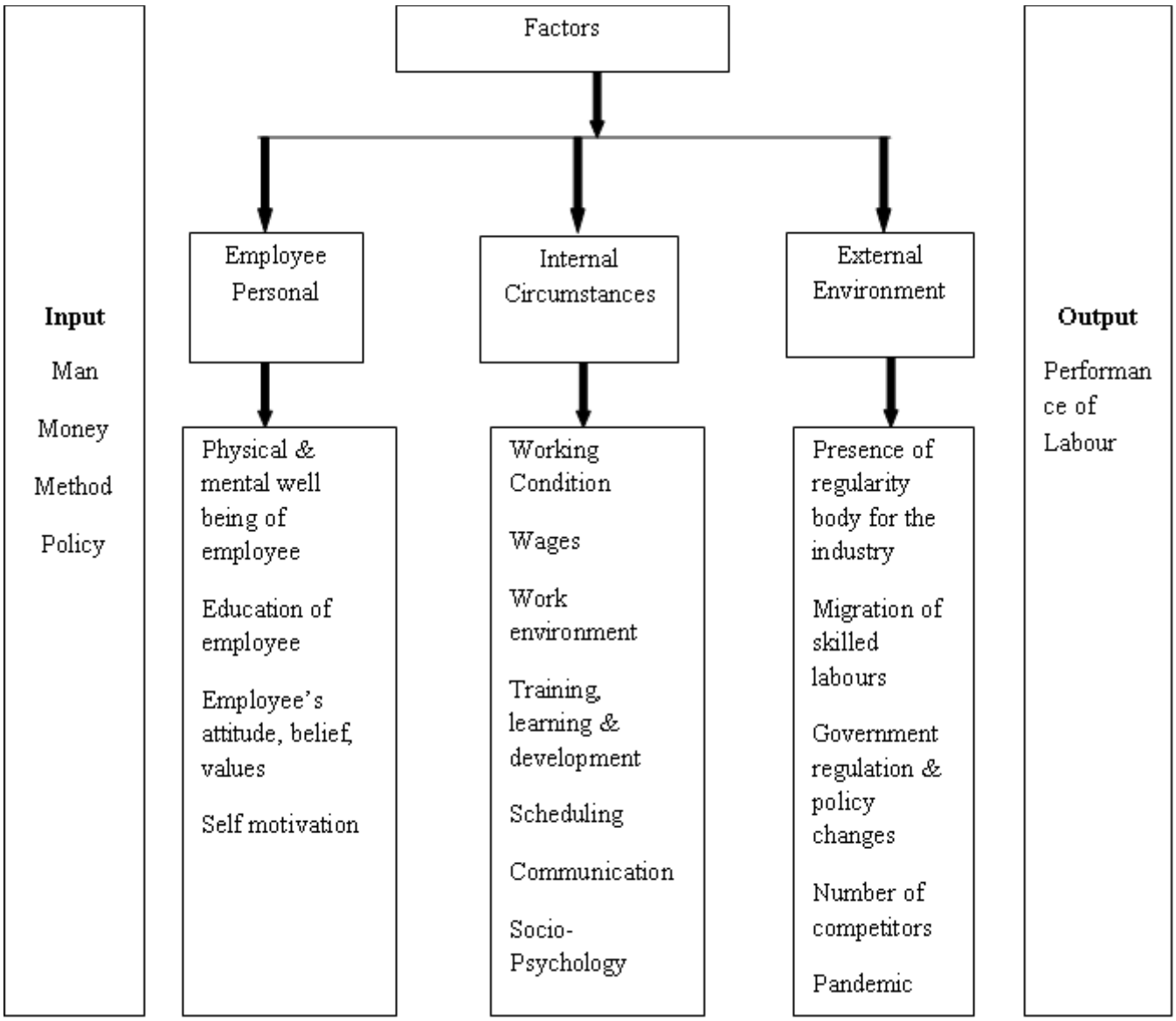

Figure 3

Theoretical Framework

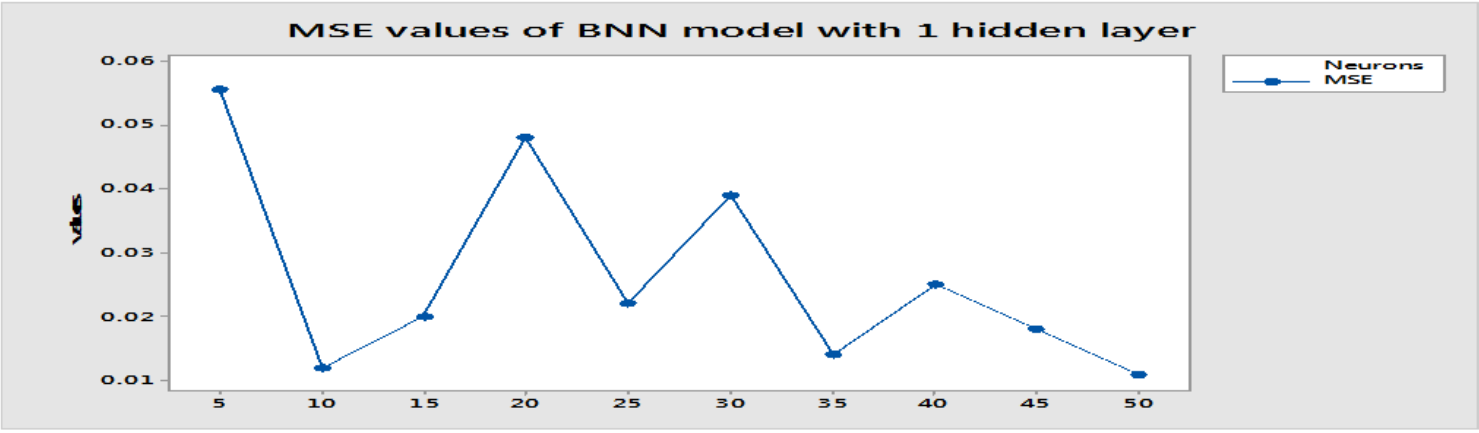

Figure 4

MSE values of BNN model with 1 hidden layer

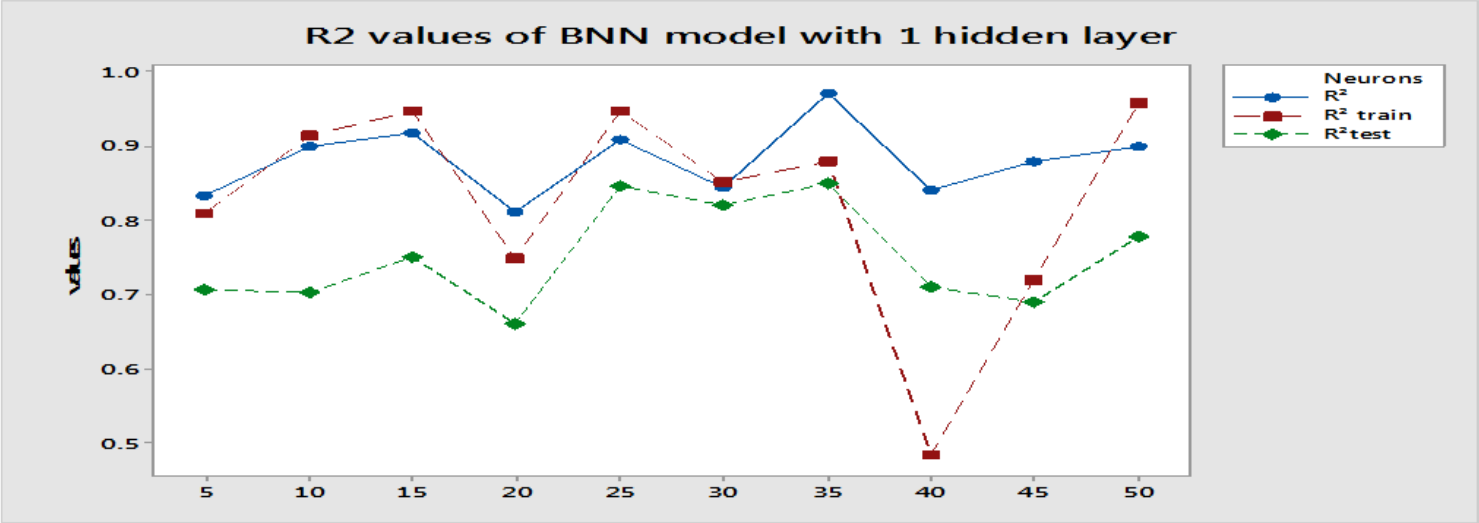

Figure 5

R2 values of ANN model with 1 hidden layer

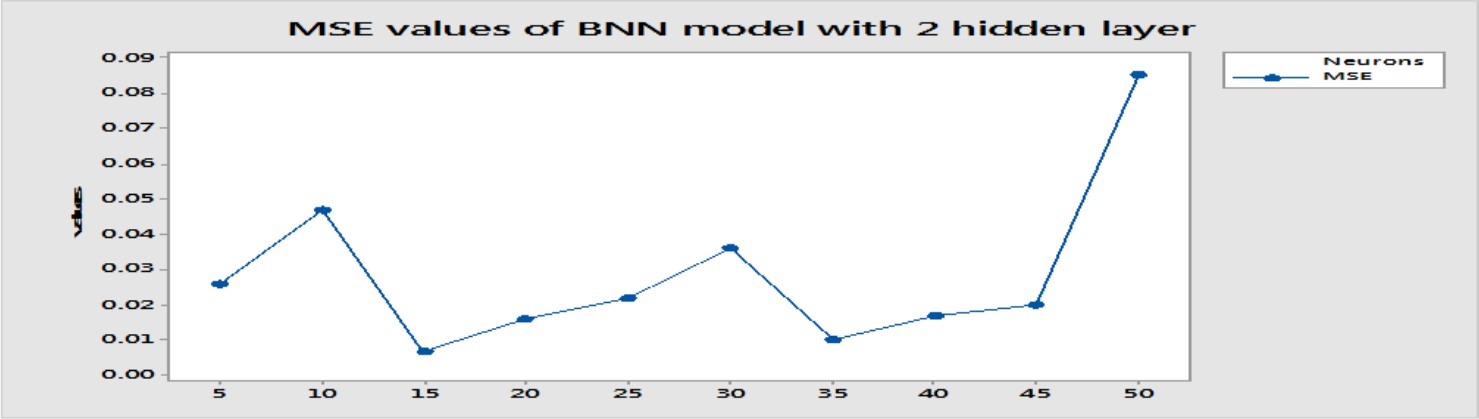

Figure 6

MSE values of ANN model with 2 hidden layers

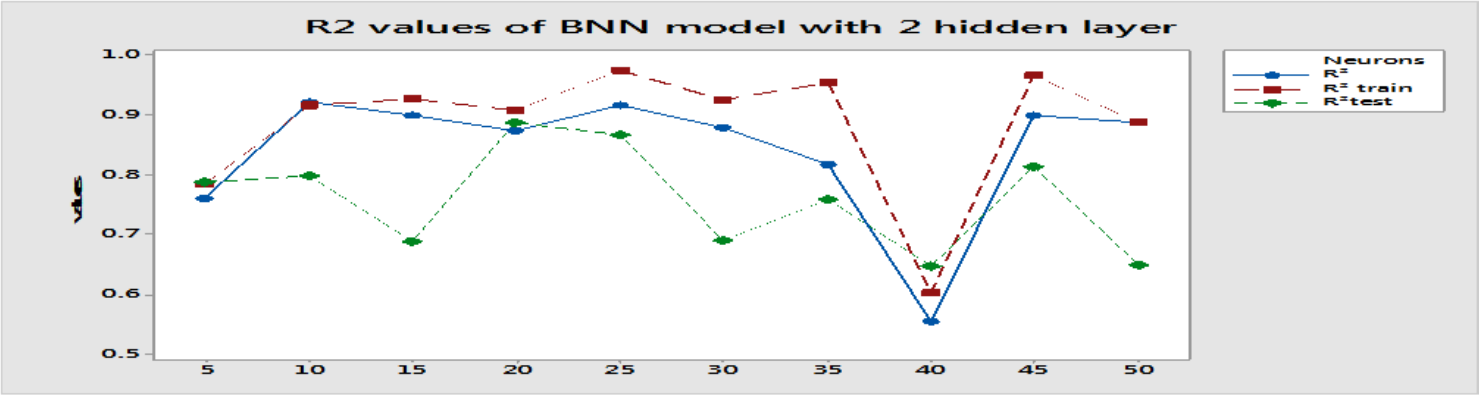

Figure 7

R2 values of ANN model with 2 hidden layers

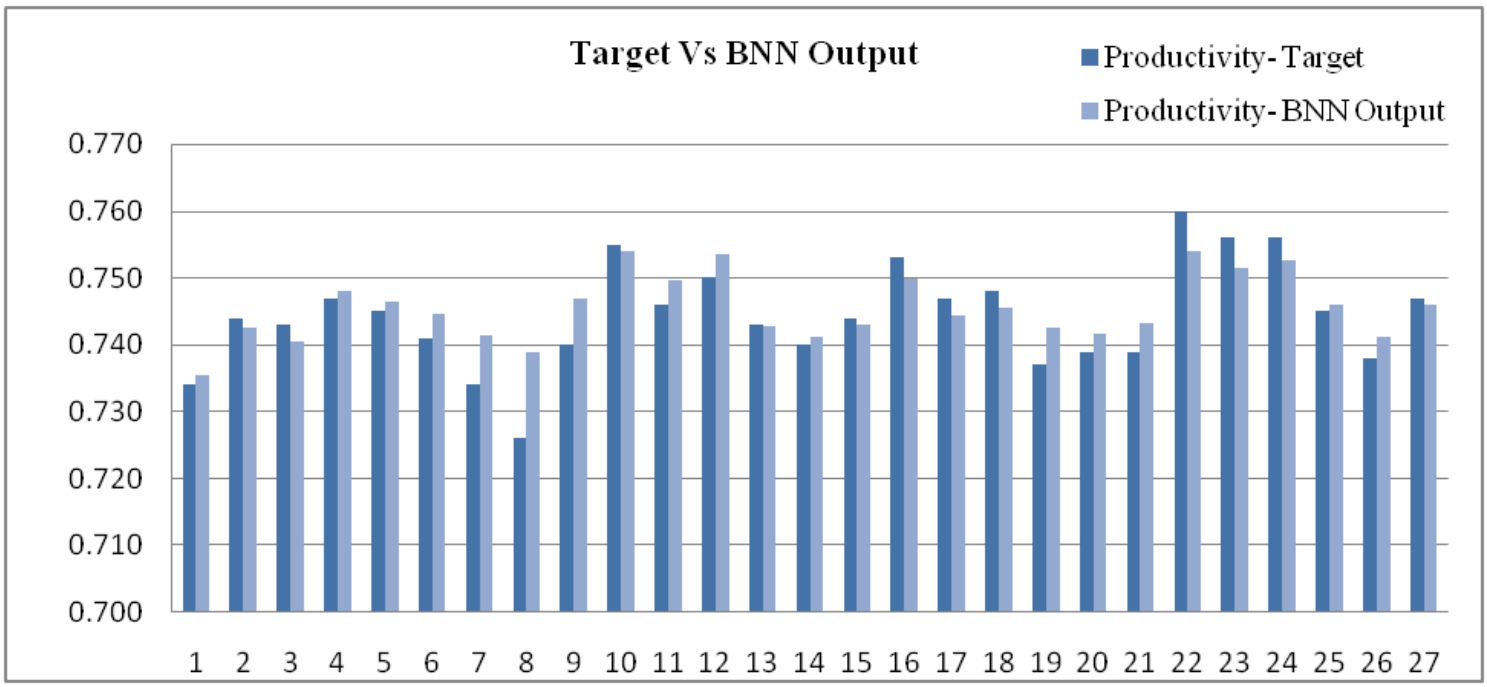

Figure 8

Target and BNN model output interpretation

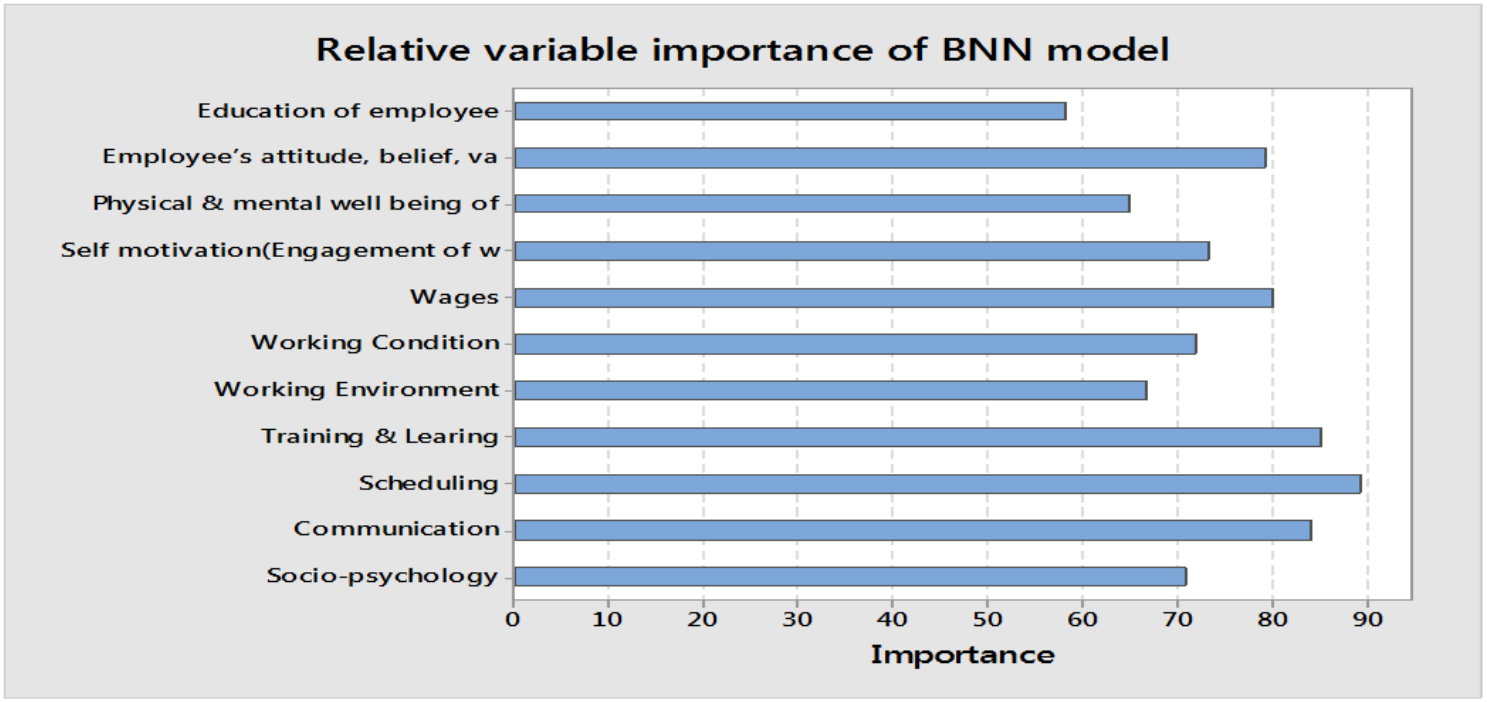

Figure 9

Relative variable importance of BNN model