



# Prediction of production facility priorities using Back Propagation Neural Network for bus body building industries: a post pandemic research article

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## Abstract

The pandemic recession has caused enormous disturbances in many industrialized countries. The massive disruption of the supply chain of production is affecting manufacturing companies operating in and around India. Particularly the medium-sized bus body building works have been reduced, due to its compound anomalies. The integrated view of the production facility priorities is not an easy task. Since it is difficult for available labour to conduct an entire project, the completion of a production process is delayed. But still, the dilemma remains as to how production managers can correctly interpret the priorities of the facility. Indeed, this is a problem missing from the previous study. Fortunately, in the current competitive environment, it is essentially needed. This study has been used Back Propagation Neural Network (BPNN) approach for predicting production facility priorities. The experimental results confirm the suitability of the model for predicting priorities. A real-world problem is taken into account in making use of the model output. In this sense, this total solution facilitates production managers in assessing and enhancing the production facilities. The findings emphasize the priority of “equipment effectiveness, labour scheduling and communication” in order to strengthen the post-pandemic production facility.

**Keywords** Production facility priorities · BPNN · Bus bodybuilding · Competitiveness · Flexibility

## 1 Introduction

The three basic human needs of food, cloth and shelter can be satisfied by farming, fabric and structure building industries. Accordingly, motor vehicle sectors contribute to human mobility and economical augmentation of India. Bus body building sector is supporting to design and fabrication of high-quality passenger vehicles that are creative in fashion and engineering, even as maintaining standards of reliability. In South India, “Karur, Tamil Nadu is a hub of bus body fabrication and doing a variety of designs also run by a huge

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enthusiastic labour force” (Annamalai et al. 2020). The following Fig. 1 explains the different stages of work carried out in the bus body building works. The bus body building production line has been interrupted due to the corona virus outbreak.

The corona virus outbreak was first reported in late 2019 and was declared a pandemic by the World Health Organization (WHO). The international environment is responding differently to the outbreak of the virus. The disruption has led to an overloading of local healthcare services (Muliyil 2020). The immediate crisis had significant long-term effects and strengthened our capacity to respond to outbreaks (Gate 2020). The worst-hit has confirmed in India as more than 700,000 cases of Covid-19 (Khanna et al. 2020). Major cities such as Delhi, Mumbai and Tamil Nadu are particularly badly affected. The hospitals are facing challenges to accommodate critically ill patients. The large lockdown in India, which started on 25 March 2020, seriously disrupted production, the economy and livelihoods. The confirmed cases of COVID-19 are booming every day. The following Table 1 gives details of confirmed COVID-19 cases.

The response to the COVID-19 pandemic around the world has required governments to introduce social distancing, lockdown, case detection, contact tracing and exposed quarantine in unprecedented ways. These measures, intended to slow down the spread of the virus. Even, the government recommended regular hand washing with an alcohol-based hand rub from the WHO’s direction, avoiding touching eyes, nose, mouth and practicing respiratory hygiene. The use of face masks for everyone, of course. The closing of mass meeting places such as schools, libraries, places of worship, malls, cinemas and the cessation of all social gatherings, sports, bus stations and community buildings are other tactics. The practice of physical distancing is shown to be a major precautionary strategy to avoid this disease. The South Indian, the state government of Kerala advised and ordered to their civilians to follow the social distancing for the next one year. The vibrant policies are recognized and evaluated based on competency in migrating infectivity and resulting in cost-effective performance. The effective vaccinations of accessible vaccines were ineffective against the current COVID-19 virus and efficient vaccines invention still over research and development (Li et al. 2020).

As a second wave, a different view of the pandemic situation has been analyzed in order to prepare precautions for the improvement of safety measures. The second wave can be most positive, but prospective individual discipline can reduce the consequences, and if the government and the frontlines are prepared to face the pandemic, it will be relatively slower (The Medical Futurist 2020). The initial response to the control of the virus in Australia is mostly successful, although the recent scenario of compliant cases in July showed fears of the second wave (Healthcare 2020). On July 15, 2020, 30 confirmed and 41 asymptomatic cases reported their very next infection in five months, following the virus peak in China. Meanwhile, between July 15 and 19, 2020, China registered 16 new COVID cases (Saxena-Editor 2020). There hasn’t been a first peak in India, only an Indian graph in a straight line. When Indians display a decrease in the instances, the second wave will emerge and can see another peak (Lalit Kant, former scientist ‘G’ and head-Epidemiology and Communicable Diseases Division 2020). In one vast wave, the virus unfolds, with no indication of seasonal influence. But it was expected that the pandemic might continue for a long time (World Health Organization 2020).

Countries are turning inwards after the pandemic by producing at the national level. These phases successfully mark the start of deglobalization. Further, industrial customer buying patterns have switched to local trading (Tsao and Pushpa Raj 2019). Thus, medium-scale industries are increasingly important in this critical circumstance. In the way, bus body building production line has been interrupted due to corona outbreak and it will take

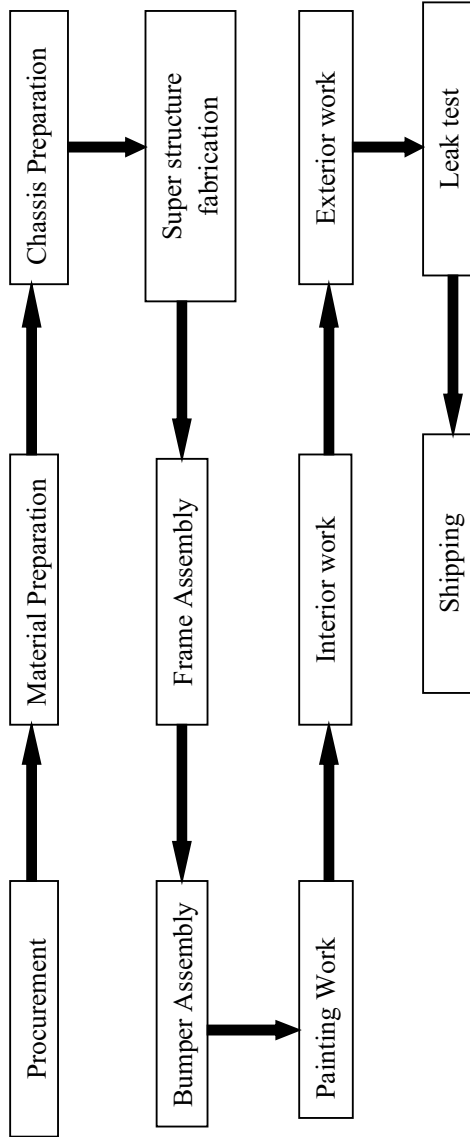


Fig. 1 Bus body building works flow

**Table 1** Country wise confirmed COVID-19 cases

Country	Confirmed COVID-19 Cases	Source
United States of America	4,862,513	World Health Organization (WHO) Nearly Globally, As of May 2021
Brazil	2,751,665	
India	1,861,821	
Russia Federation	861,423	
South Africa	516,862	
Mexico	443,813	
Peru	433,100	
Chile	361,493	
Spain	344,134	
Colombia	327,850	
Iran	312,035	
United Kingdom	305,623	
Italy	248,229	
Turkey	233,851	
Germany	212,320	
France	191,295	
Total	14,268,027	

time to become fully functional. These industries are now in a position to create a sustainable production chain and to reorganize the work system. The industry can tackle the current scenario through efficient production management. This is essential for the long-term survival of companies. However, there is a significant obstacle in implementing these management techniques in efficient manner. Because, the integrated view of the production facility priorities is not an easy task. Likewise, several managers do not have the expertise to investigate prioritization. According to the literature, only the importance index can be used to calculate factors affecting labour productivity. However, this strategy does not provide precision when prioritizing production facilities. Therefore, the significant influence of this study promotes the development of a model based on productivity index calculations and Back Propagation Neural Network (BPNN) to prioritize the manufacturing facility. This also improves production managers' performance in terms of priority. Based on the literature, the BPNN model has been chosen to construct a prediction model. For data training, this model employs Bayesian regularization and the back propagation algorithm. This improves the expected performance of production facility prioritization.

## 2 Review of related studies

The official definition of productivity is defined as, "proportion obtained by dividing output by one of the input factors" in 1950 (Organization for European Economic Cooperation (OECE) 1950). Table 2 reflects the definitions of productivity.

Productivity is a major factor in successfully completing of every project's. As a consequence, the term can be interpreted as "Quantitative evaluation of the correlation between the

**Table 2** Definitions

Time Scale	Definition	Reference
Eighteenth century	The word productivity appears in article for the first time	Organisation for European Economic Co-operation (OECE) (1950)
Nineteenth century	Faculty to produce	Fabricant (1962)
Twentieth century	Relationship between output and the means employed to produce this output	Bernolak (1997)
Twenty first century	A family of ratios of output to input	Song and AbouRizk (2008)
	Total factor productivity is ratio between total output to measures the combined input factors of labour, materials, equipment, capital, design	
	The ratio of tangible output to the tangible input	Sumanth (2011)
	The quantity of work produced per man-hour, equipment-hour, crew-hour worked	Durdyev et al. (2012)
	The ratio between completed work and expanded work hours to execute the project	Nasirzadeh and Nojedehi (2013)
	Real output per hour worked	Calcagnini and Travaglini (2014)
	Ratio of output quantity to quantity of inputs	Gerek et al. (2015)
	Amount of goods produced within a labour unit	Wolfjfer et al. (2019)

weighting value and the respondent's value." The labour force is a significant contributor to the productivity of global manufacturing in post-pandemic circumstances. (Deshmukh and Haleem 2020). This survey consisted of an effective evaluation of the various studies that have been conducted influencing the productivity of labour. Table 3 presents various studies, independent factors and methodologies that affect the productivity of labour force. This reveals that, the different kind of techniques has been used to forecast labour productivity in successful manner. Even though, facility prioritization is difficult to predict in the pandemic scenario. Since more effort is needed and sustainable factors need to be quantified.

In general, AI-based neural network algorithms have been demonstrated to be an excellent predictive tool (Patel et al. 2017), as evidenced by particle size prediction (Gautam et al. 2021), equipment effectiveness prediction (Sivakumar et al. 2022), and paper industry performance prediction (Jauhar et al. 2022). Likewise, the robust search algorithm of Back Propagation Neural Network (BPNN) also a good technique for predicting facilities (Zhang and Qu 2021). The BPNN technique was used in numerous studies, such as cooling output forecasting (Han et al. 2019), production schedule of clinical masks during a pandemic emergency (Wu et al. 2020), prediction of priority polling (Yang et al. 2021), and time serious forecasting (Erzurum Cicek and Kamisli Ozturk 2021). Furthermore, in the pandemic Covid-19 situation BPNN technique has been used to forecasting of U.S oil markets (Wu et al. 2021a, b). Likewise, ARIMA method used to forecast the US stock market progresses (Singh et al. 2021), Convolutional neural network method used to forecast crude oil price (Wu et al. 2021a). The definition, advantages and disadvantages of the different models can be expressed in Table 4. Based on these, the BPNN model has been chosen to construct a prediction model.

### 3 Methodology

Initially, the review crew has been organized with professionals of varied backgrounds. The crew organized with 10 members of a professional with high educational qualifications and experience and crew guided to strictly follow the research procedure while observing and mapping data, of course, they have been given some flexibility. The crew shall analyze the labour efficiency of the work for the period from July 2019 to January 2020. Unfortunately, after December, the situation in China changed as a result of the covid-19 pandemic. It was also reflected in Tamil Nadu, India, in March 2020. The government declared a lockdown to monitor the state of emergency. The government gave some relaxation later in May 2020 to carry out the work. The situation decreases the productivity of the company even more. In the meantime, management is under stress to protect the company's labours and production efficiency. As a result, the same crew was again formulated at the beginning of July 2020 to find a solution to the current and post-pandemic situation. In addition, the benefits found in the literature have been used here by to develop a prediction model based on BPNN. The deeper representation of the modeling technique is shown in Fig. 2.

## 4 Model development

### 4.1 Influencing factor identification

Initially, the crew randomly picked 30 completed works (before pandemic condition) to determine the Labour Productivity (LP) which reflects an average value of 64%. Secondly,

**Table 3** Different factors affecting labour productivity and methodology used

Industry	Methodology	Optimization	Productivity affecting factor	Measurement calculation	Reference
Construction	Neural network (NN)	Labour productivity	9 factors identified	Importance Index	Dissanayake et al. (2005)
Construction	System dynamics modeling	Labour productivity losses	Endogenous & Exogenous variables	Not involved	Enshassi et al. (2007)
Economics	Bayesian linear model	Capital & labour productivity	Labour & Capital efficiency	Not involved	As'ad et al. (2015)
Manufacturing (Steel rolling mill)	Fuzzy mixed integer bilinear program	Master production schedule	Production plan	Not involved	Späth (2016)
Manufacturing	FLOPACE Model	Labour productivity	20 factors identified	Important index model	Goel et al. (2017)
Construction	Artificial neural network (ANN)	Project performance	16 factors identified	Importance Index	El-Gohary et al. (2017)
Construction	Computational Intelligence	Labour productivity	7 factors identified	Performance Indicator	Alaloul et al. (2018)
Construction	Panel survey ranking using SPSS	Labour productivity	35 factors analyzed by 3 categories	Relative importance index	Golharaghi et al. (2019)
Construction	Panel Ranking	Labour productivity ranking	45 factors analyzed & 6 identified	Importance Index	Ponnalar et al. (2020)
Incumbents firms	Regression model	Employment type & time of work	Non-standard work forms & working time	Not involved	Al-Kofahi et al. (2020)
Construction	Dynamic modeling	Labour supply chain	Skilled labour shortage	Not involved	Kim et al. (2020)
Construction	Neuro fuzzy system	Production rate	Complex relationship between variables	Not involved	Gerami Seresht and Fayek (2020)

**Table 4** Different ANN models

Model	Mathematical programming models	Different ANN models	Back propagation model
Description	Linear, Non linear, Integer programming, dynamic programming	General Regression NN, Radial Basis Function NN, Adaptive Neuro Fuzzy Information System, Elman propagation algorithm	Backward propagation of errors is an algorithm for supervised learning of AI network using gradient descent
Literature	Al-Kofahi et al. (2020), As'ad et al. (2015), Kim et al. (2020), Noda and Kyo (2015)	Dissanayake et al. (2005), El-Gohary et al. (2017), Goel et al. (2017), Golnaraghi et al. (2019)	Alaloul et al. (2018), Golnaraghi et al. (2019)
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
Disadvantages	Difficult to formulate. The gradient-descent in load minimum	Unrelated calculations to evaluate new inputs cannot be ignored	Random search is time consuming



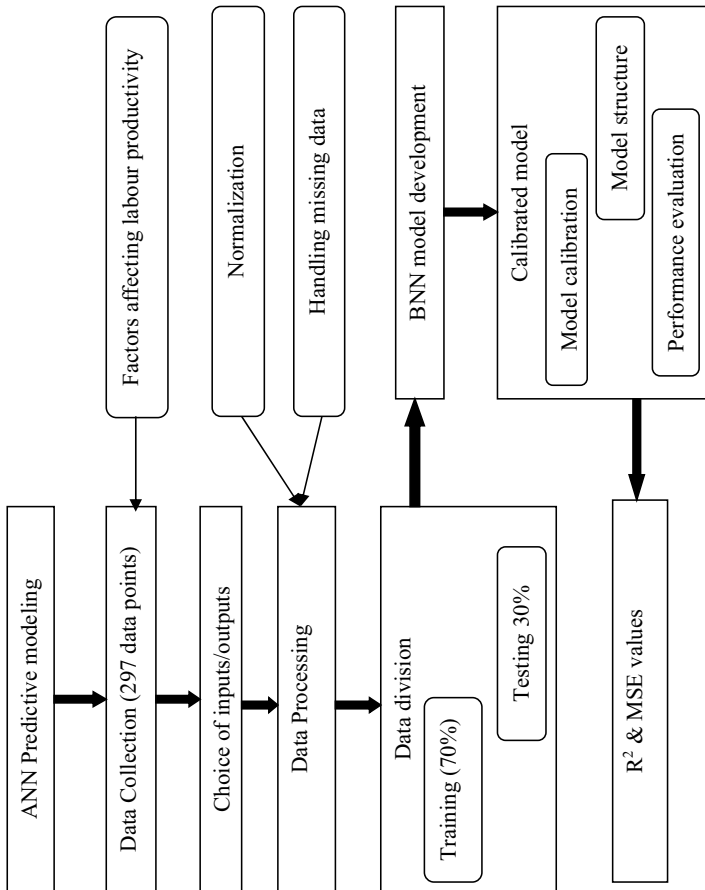


Fig. 2 Model development flowchart

the crew carried out the same test for a random sample of 5 completed works (after industrial reopen) and found that LP had been reduced to 36 percentages. There is a lack of efficiency in the bus body building sector, and the importance of this issue has been emphasized in the post-pandemic scenario. The crew, therefore, agrees to identify the factors affecting LP in the industrial sector. The literature is being reviewed and the crew identified 16 factors. A few factors are selected from the literature by the review crew to address this challenge, with a focus on identifying the priorities of the production facility. The selected factors are formalized causes of industry bad image (Dainty et al. 2005), employee attitude, belief, values and socio-psychology (Mojahed and Aghazadeh 2008), scheduling and self-motivation (Kazaz et al. 2008), communication (Noda and Kyo 2015), physical and mental well being of employee, working condition, education of employee, wages, work environment, number of competitors, presence of regularity body for the industry, Government regulation and policy changes (Goel et al. 2017), migration of skilled labours (Kim et al. 2020). In addition, two additional factors are identified by the crew as the effectiveness of the equipment and the external pandemic situation in order to strengthen this research.

The representation of the theoretical framework shows the relationship between interconnected variables and is being used in the open framework analysis. The theoretical work of the system on the categorization of factors is shown in Fig. 3. Besides, to simplify the research, the factors categorized by 3 subgroups are as follows:

1. Employee's personal
2. Internal circumstances
3. External environment.

The categorization is created based on factors influencing the industrial sector's labour productivity.

## 4.2 Data collection

Three groups of 50 members have been created, each with a combination of staff, supervisors and managers from leading manufacturing industries from the South Indian hub of Karur, Tamil Nadu, India, to facilitate the panel's response. Members gathered from 30 industries selected at random; those industries must have a workforce of around 100 to 150. Further strengthening the study in the context of the post-pandemic situation, the crew agreed to restrict the performance analysis to employee's personal and internal circumstances. A normalized weighting factor (Goel et al. 2017) method is used to measure the productivity index and a total of 297 datasets have been developed for further study. The formula used for calculating the productivity index is expressed by Eq. 1–4. The equations of 5–7 used to generate descriptive datasets as illustrated in Table 5.

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

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

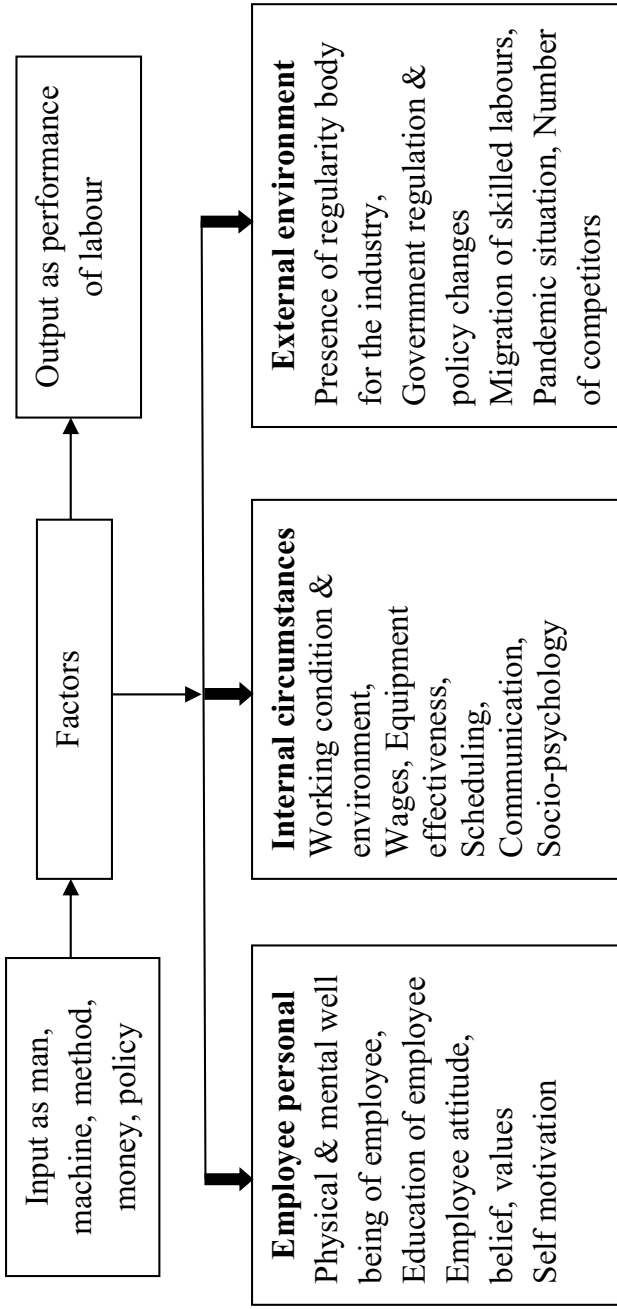


Fig. 3 Theoretical framework

**Table 5** 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	Equipment effectiveness	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

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

$$\text{Factor rating received from respondents} = \sum \left[ \frac{\text{Rating of each respondent}}{\text{Maximum rating possible} \times \text{number of respondent}} \right] \quad (4)$$

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

$$\text{Standard error of sample mean SE } \bar{x} = \frac{\text{Population of standard deviation } (\sigma)}{\text{Total number of elements } (\sqrt{n})} \quad (6)$$

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

### 4.3 Correlation analysis

The intensity and direction of the linear relationship between the database variables Pearson correlation coefficient procedure has been used. Correlation coefficients are in the range-1 and +1. The higher unconditional coefficient end results in a better association of variables. Considering this case, an exact value of 1 can be shown that the ideal linear relationship and 0 state the nonlinear relationship between variables in the Pearson correlation system. Table 6 indicates that perhaps the correlation among parameters is computed to be close to 0 most of the time. As a result, none of the relations are really similar and there is no over-inference experience.

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

### 4.4 Constructing Back Propagation Neural Network model

The BPNN is an ‘AI’ approach that replicates the function of the human brain. The ‘NN’ could be represented as a mathematical model of human neural architecture due to their learning and generalization capabilities. A ‘NN’ can be used whenever there is a relationship between input and output variables. The BPNN is a type of supervised learning. Its output results are forwarded, while errors are propagated backward. The BPNN has three layers: input, hidden, and output. Input layer is responsible for receiving data from the outside domain. The input data could be normalized to enhance the outcomes. Hidden layer, which is made up of neurons, is responsible for converting the input into a format that the output can understand. Output layer, which is similarly made up of neurons, is responsible for producing and presenting the output results. The general design process of the BPNN model is shown in Fig. 4.

**Table 6** 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

In this study, the BPNN prediction model is utilized for unknown function approximation. The network has two hidden layers each providing the optimal forecasting results. Then ideal inter relation along with input variables and output variables can be determined by training datasets addition to predicting the output for new input variables. Herein, the three phases (training, validating, testing) of BPNN model scrutinized with 297 data points and randomly divided of 70% and 30%. However, the number of neurons varied from five to fifty and hidden layers from 1 to 2. The Bayesian Regularization (BR) algorithm has been used for data training to achieve the best network structure. Besides, validation sets are approximate capacities for network generalization and an independent network efficiency index has been analyzed in the test phase.

### 5 Results and discussion

The analysis suggests that the industrial situation relates to the bus body building industry during the post-pandemic situation. Due to the enormous labour intensity and a variety of variables, the labour productivity estimation of the bus bodybuilding sector is extremely difficult. Based on the findings, the designers concluded that the proposed model produces appropriate and successful results. To examine the models' performance statically, the coefficient of determination ( $R^2$ ) and Mean Square Error (MSE) were used as error metrics. The statistical analysis of the  $R^2$  value varies from zero to one and measures the number of variations between the predicted and the target values. The performance index of the BPNN model  $R^2$  and MSE assesses the interpretation by mapping as per the subsequent Eqs. 9–10, wherever ' $t_i$ ' represents the target value while ' $o_i$ ' represents the output value.

$$R^2 = 1 - \left( \frac{\sum_i (t_i - o_i)^2}{\sum_i \left( t_i - (1/n) \sum_i t_i \right)^2} \right) \tag{9}$$

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

The performance index of the BPNN model refers to 1 and 2 hidden layer and is shown in Table 7, Furthermore, graphical representation of MSE and  $R^2$  variation with respect to neurons is depicted in Figs. 5a, b and 6a, b respectively.

The rational quantification of  $R^2$  and MSE values suggest that two hidden layers and 20 neurons are the ultimate configurations, demonstrating the highest precision for predicting output results. The model had a MSE and a significance index of 0.016 and 0.889 for  $R^2$  results. Figure 7 demonstrates the relationship between the aim and the BPNN output values as perceived. The relationship inferred that the forecasted values are very close to the actual data. This is concentrated and stated as 0.016 from a prediction point of view and MSE is found to be small in error. The  $R^2$  test value is 88.9%, which indicates that the model is capable of predicting the priorities of the production facility with 89% accuracy. The  $R^2$  has been proved with Eqs. 11 and 12 in model chosen. The ranking of functional variables is shown in Fig. 8.

$$\text{Training fitted line for output} = 0.66 \times \text{Target} + 0.25 \tag{11}$$

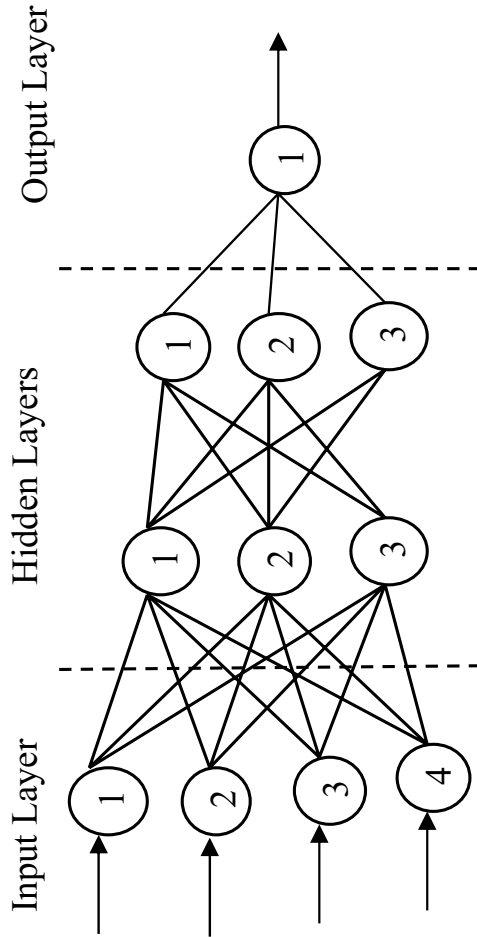
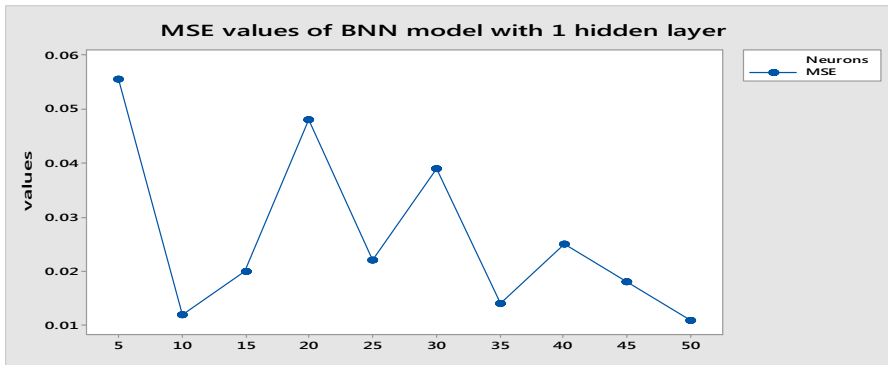


Fig. 4 General architecture of BPNN model

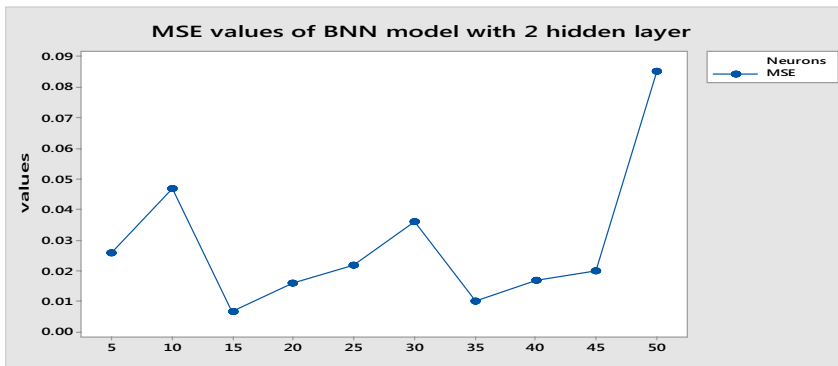


**Table 7** Performance Indices for models with 1 hidden layer

Neurons	5	10	15	20	25	30	35	40	45	50
Performance Indices for models with 1 hidden layer										
MSE	0.0555	0.012	0.02	0.048	0.022	0.039	0.014	0.025	0.018	0.011
R <sup>2</sup>	0.8325	0.899	0.918	0.811	0.909	0.844	0.972	0.841	0.88	0.9
R <sup>2</sup> train	0.81	0.914	0.947	0.749	0.947	0.852	0.88	0.484	0.72	0.958
R <sup>2</sup> test	0.707	0.703	0.751	0.66	0.847	0.82	0.849	0.71	0.69	0.778
Performance Indices for models with 2 hidden layer										
MSE	0.026	0.047	0.00677	0.016	0.022	0.036	0.01	0.017	0.02	0.085
R <sup>2</sup>	0.761	0.922	0.901	0.875	0.917	0.879	0.817	0.5559	0.901	0.888
R <sup>2</sup> train	0.785	0.918	0.928	0.908	0.976	0.926	0.955	0.603	0.968	0.888
R <sup>2</sup> test	0.789	0.7992	0.689	0.889	0.867	0.69	0.76	0.648	0.814	0.649

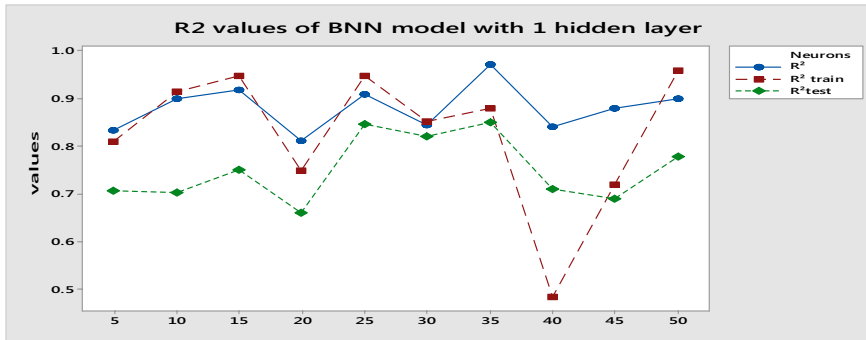
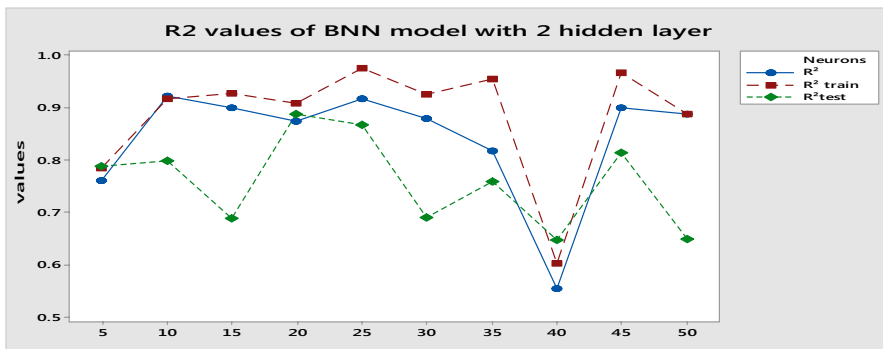


a: MSE values of BNN model with 1 hidden layer



b: MSE values of BNN model with 2 hidden layer

**Fig. 5** a MSE values of BNN model with 1 hidden layer. b MSE values of BNN model with 2 hidden layer

a: R<sup>2</sup> values of ANN model with 1 hidden layerb: R<sup>2</sup> values of ANN model with 2 hidden layerFig. 6 a R<sup>2</sup> values of ANN model with 1 hidden layer. b R<sup>2</sup> values of ANN model with 2 hidden layer

$$\text{Test fitted line for Output} = 0.38 \times \text{Target} + 0.46 \quad (12)$$

## 5.1 Managerial insights

The primary driver for dynamic growth and the development of the country's prosperity has been recognized as production. Triggers of production require everything from raw materials to finished products. The manufacturing sector has offered employment, both directly and indirectly. All-powerful nations have been focusing on a combination of traditional production facilities, automated special uses and industry 4.0 in the post-pandemic scenario. Industries could never decide to bypass the conventional production base. The pandemic has prompted us to look at affordable prices and people-based automation, which will encourage the company to play its socially responsible role. Labour expertise, labour quality, efficient pricing and supply chain networks generally drive international competition. The same had been highlighted in most previous studies. Unfortunately, the problem of uncertainty estimation has been addressed without recognizing the facility's priority in the emergency. In this analysis, our proposed model allows production managers to

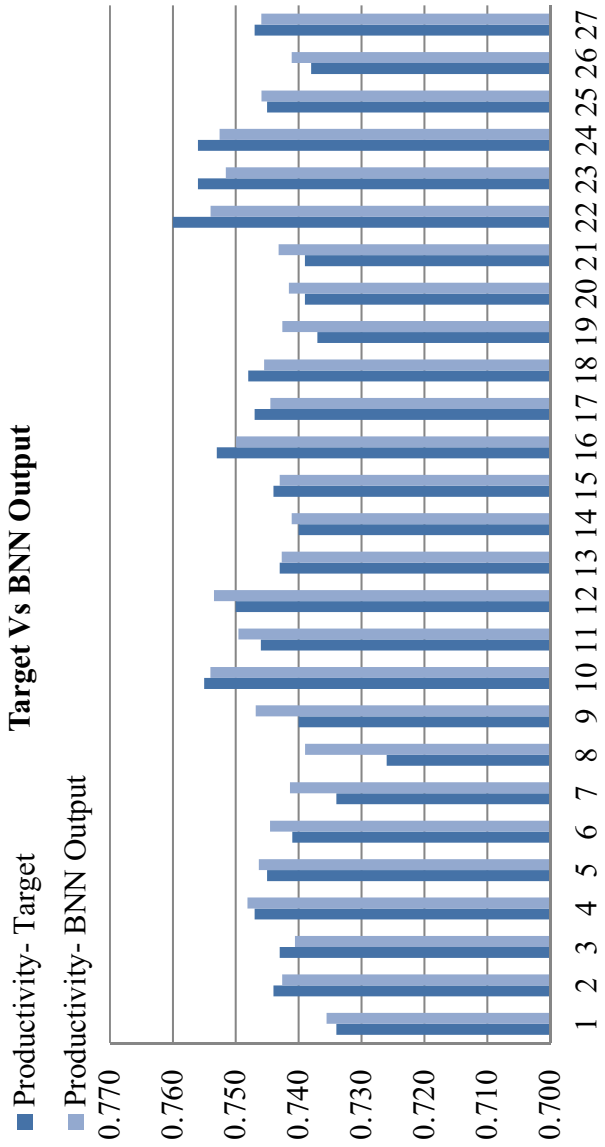


Fig.7 Target and BNN model output interpretation

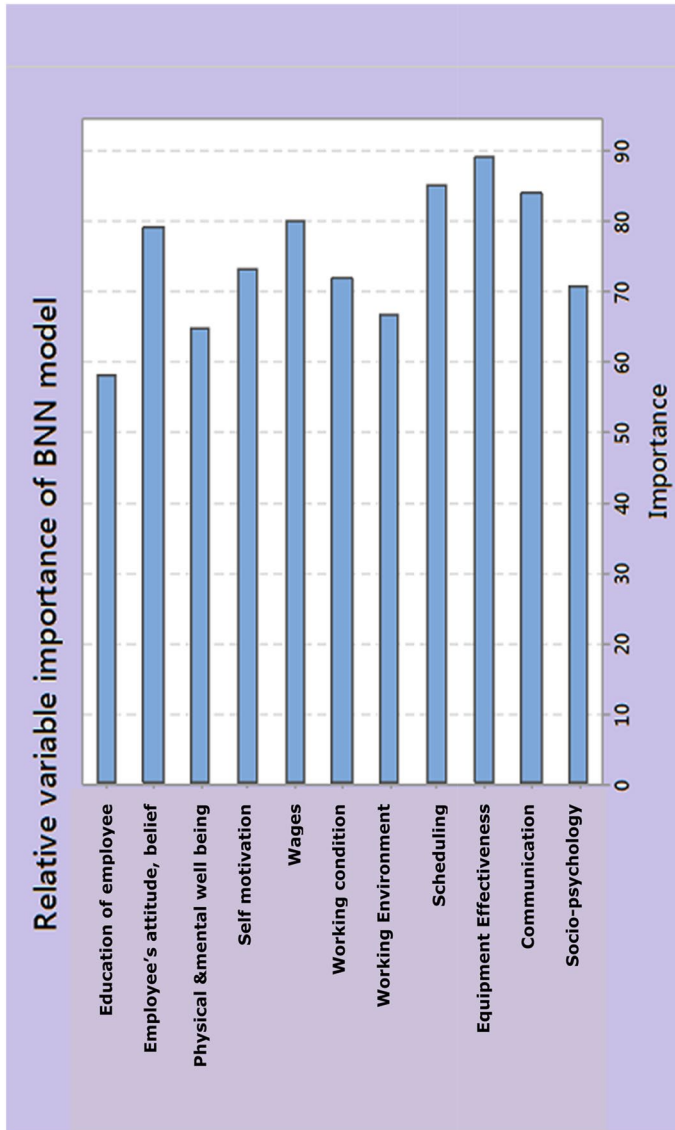


Fig. 8 Relative variable importance of BPNN model

function efficiently even in pandemic and emergency times. In crucial situations, the proposed model encourages production managers to make the right decisions. To gain broad insights, we examined distinct parameters and calculations of productivity index. To prioritize the parameters, the theoretical framework has been used. To predict facility priority, the powerful predictive tool of the back propagation technique has been used. The ranking analysis enables managers to choose the necessary priority to promote the achievement of optimum performance. The proposed model illustrates that the organization's productivity will be increase by the contribution of production facility priority towards equipment effectiveness, labour scheduling, and communication between the workforces.

## 6 Conclusion

The purpose of this study is to propose a prediction model for prioritizing production facilities. Based on literature, only the significance index can be used to calculate factors affecting labour productivity. However, when it comes to prioritizing production facilities, this strategy is ineffective. Thus, this study proposes BPNN prediction model based on productivity index estimates. Initially, the review team identified 16 variables influencing labour productivity and selected 11 for this investigation. The panel responses have been used to calculate productivity index. In response to the results of these calculations, the BPNN model has been developed. Furthermore, statistical results reveal that the proposed model can predict with an accuracy of 89%. In addition, proposed BPNN model's findings were utilized to rank the relative variables in order to prioritize the production facilities. According to the findings of this thorough investigation, the first focus should be given to equipment effectiveness and scheduling of labour. In addition, the experimental results confirm the suitability of the model to predict the priority of the production facility in the area of bus bodybuilding. Further, proposed BPNN prediction model facilitates the production manager's to assess the production facilities. To achieve a realistic quantification, production managers must develop the improvement plan based on prioritizations results. Also, production managers must communicate the importance of prioritizations and improvement plan in maximizing production performance to owner and entire production squad.

Furthermore, this section discusses the limitations of the current study as well as an attractive future direction. The proposed BPNN superiority model developed based on Bayesian Regularization (BR) algorithm. This has the ability to immediately improve task performance. However, it has only used BR algorithm for data training to achieve the best network structure. Hence, few other hybrid algorithms can be given more strength in developing prediction models.

### 6.1 Social significance of this study

Productivity is the primary source of competitive advantage for the engineering firm, especially in the bus bodybuilding industry. People, machines, materials, capital and methods are the main sources of productivity in the industry. Pandemic recession reduces the contribution of sources of productivity. The panic condition reduces the livelihood of the community. The optimal "production facility priority prediction model" is proposed in this paper to increase efficiency in the bus bodybuilding industry. The proposed model helps the bus body building production manager to make the required decisions during the evaluation of the production facilities. This evaluation has been reorganized as the driving force

of vibrant productivity growth in the selected sector as well as the development of the wealth of society. The significance of the community's livelihood in post-pandemic can be accessed from the following:

1. The bus body building industry has the potential to provide people with direct and indirect employment opportunities. This is particularly important because of the serious increase in employment across nearer of industries societies.
2. The performance of the machinery will be improved by the required method of maintenance. This will increase the efficiency of machinery, the jobs of maintenance professionals and the business of retailing.
3. Entrepreneurial spirit and employability in retail services would be stimulated. Retail businesses contribute primarily to the materials supply chain sectors. This would increase the economic turnover and growth of the individual population.
4. The prescribed model improves the production facilities by proper scheduling, equipment performance and communication. The revised framework would standardize company methods related to improving efficiency. This will further develop industrial society.

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**Data availability and material** The data associated with a paper is available.

## Declarations

**Conflict of interest** The authors declared no potential conflicts of interest for the research, authorship and publication of this article.

**Consent to participate** The authors voluntarily agree to take part in this study.

**Consent for publication** The authors gives consent for the publication of identifiable details, which can include photograph(s) and/or videos and/or case history and/or details within the text ("Material") to be published in the above Journal and Article. Therefore, anyone can read material published in the Journal.

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