Neural Network Approach For Making Foundry Industry Sustainable

Ranjitsinh A Deshmukh, Dr. Rahul B. Hiremath

Abstract: Global casting production reached 104.4 million tons in 2016. Nearly 47.2 million metric tons of casting produces by China. Casting production increases from 5.4% to 11.35% million metric tons. USA, Japan, Germany, Russia, Korea, Mexico, Brazil and Italy are the top ten nations. Approximately 26 million Micro, Small and Medium Enterprises (MSMEs) provide 60 million people employment in the Indian economy. Almost 6500 foundry units are in country out of which 90% can be categorized as small scale units, medium scale units as 8% and large scale units as 2%. Nearly 6500 enterprises in India located at 47 urban clusters. There are some challenges in front of foundry industry such as energy consumption, environmental, Occupational Health and Safety and sustainability. But some new projects have been scaling up MSME clusters in India to make it sustainable. It enables the adoption of social services and sustainable challenges in business. Foundry industry complex relationship between different parameters can be modeled by using neural network. It can also study running such program lead to substantial improvements in targeted industry and make it sustainable industry.

Keywords: Neural network, sustainable, Occupational Health and Safety etc.

1 INTRODUCTION:

The business becomes successful because of its manpower and their skill, attitude and their satisfaction towards work they carry out. The worker should feel secured and must have a good health is an important factor to be concerned in Corporate Social Responsibility; this becomes diverse when the workers have to carry out the tasks in which risk is involved. The organization must have a clear picture of how to build a safe and healthy environment for the workers. Sustainable growth is achieved through safe, healthy environment of the organization. Currently there are a lot of industries which are concentrating on the occupational safety and health of the workers to get globally competent. The work related injuries and the resulting diseases are the problem faced by the organizations worldwide. As far as business competition is concerned the sustainability becomes the major factor. It is important for the management to know the factors which control the sustainability. The researcher's key point of interest is the sustainable development; it is shown by the research that sustainable development can best predict turnover of an organization. Retaining of the manpower is indeed the maximization of the profit. Thus the sustainability is the factor of concern to satisfy green foundry. Satisfaction of employee also controls the external customer's view towards the quality of service/product. Thus unsatisfied employees can harm the external customer's satisfaction; hence the management must provide equal importance to both the external as well as internal customers' satisfaction. Thus currently the situation is to consider the employees as a major asset of the organization. The management is surely responsible for providing the safe working environment. Thus there is need of the management to realize the importance of the green foundry and must be committed to promote the same. Regular training must be provided to employees and frame a methodology for providing the harmless environment. It is worth to note that good health always lead to good business for the organization. Sustainable designed work atmosphere may result in the reduction of absenteeism due to illness leading to less loss in productivity of an organization. Dejoy et al. in their work mentions that the attitude of employee plays a major role in the safety related issues. The accident does not only harm the human resource but also results in the monetary losses due to the interruption of the processes, machinery damage diluting the reputation of the firm. The organizations understand the cost related to the health and the injury through the economic analysis with the help of safety performance measurement system if being implemented. Not only the economic factors but also the non-economic factors like the culture or any other existing system must be considered during the assessment of the workplace safety.

2 Data Collection

The questionnaire used in this study contained 24 items and the respondent needed to provide response to all the questions using 1 to 5 Likert-type scales (1-strongly disagree and 5-strongly agree). The responses are collected from workers of different textile industries in Solapur through personal contacts. The awareness on 24 items from respondents in concern to occupational health and safety is collected. The probability and also the non-probability sampling are used for the selection of industries. Stratified random sampling was used under the probability sampling. Random selection of the units for the study is carried out based on based on similarity in certain characteristics.

3 FACTOR ANALYSES

Factor analysis has been carried out where one ninety nine responses were tested and the validity as well as the reliability of the scale was tested. The variable testing was conducted with the help of factor analysis on 199 responses by using the principal component method followed by varimax rotation to make sure the importance and suitability of the variables to use SPSS model. The algorithms for Principal Component Method Factor Analysis and varimax rotation can be found in the respective appendix. The categorization of the items was carried out in six factors including the different variables to measure the relation between the performance of the firm and the occupation safety as found out by the workers. These six factors are defined as Environmental, Social, Economic, and Health. Items with factor loading of more than 0.5 are considered for further analysis. The Cronbach's Alpha (α) was computed for the internal consistency of the actual survey data, the value is 0.80 which above the acceptable value of

0.70 highlighting the internal consistency of the scale established [184]. As a measure of the sampling adequacy the value of Kaiser-Meyer-Olkin (KMO) was computed and found to be ------- indicating the proceeding of the factor analysis correctly and the samples are sufficient as the minimum acceptable value of KMO is 0.5. The Bartlett test of sphericity results indicates that it is significant that the factor analysis processes is correct and appropriate for testing multifactorality. Therefore, the statistical tests provided that the anticipated items and all factors of the instrument are sound enough for analysis. TABLE OF FACTOR loading SCORE

4 ARTIFICIAL NEURAL NETWORKS (ANN)

With the beginning of modern technology and information science, classy information systems can be developed to make predictions or decisions depending on information contained in the accessible data. These are called learning systems and are now-a-days used for the reason of classification and prediction. The systems such as word recognizer, process monitor, signal stabilizer, risk analyzer and sonar classifier are the early stage applications of the neural network. Neural networks are good in identifying patterns or the data trends, and also best for the prediction and forecasting in the areas of Sales, Consumer research, marketing, management of risk, process control in the industries. Some other applications as per the literature include manufacturing, advertising, medical tourism, securities market, banking and portfolio management. An ANN is a model of processing information that is motivated by the way biological nervous systems, like the human brain, process information. The major element is the new structure of the system for information processing. It composes of a big number of extremely interrelated processing elements (neurons) working in combination to provide solution to specific problems. ANNs, learn by example as peoples do. An ANN is needs to be constructed for a definite application say data classification or pattern recognition by a learning process. As per the biological system learning incorporates tuning to the connections that are present between the neurons and is also found in ANNs as well. It is a network of neurons Where all neurons are linked with input, weight equivalent to the input, scalar bias, a transfer function and an output as shown in figure , X_j 's and W_j's are known as inputs and weights. The network consists of more than one neuron in every layer. The end layer is the output layer and the first layer is input layer and the layers between these are the hidden layers. The output of one layer is the input for the next layer as far as hidden layers are concerned. For solving variety of problems multilayer network are very useful and powerful tool. Different types of networks are available for various purposes. For the current study an attempt has been made to use multilayer back propagation neural network architecture for the OHS.

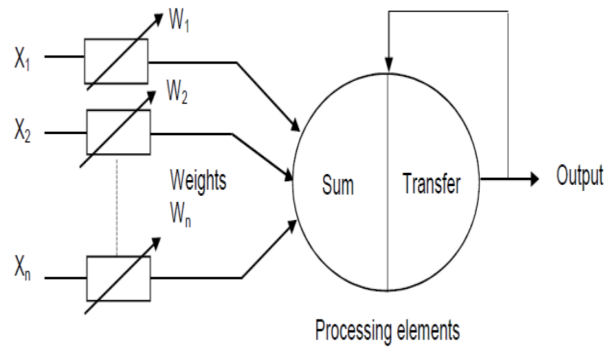
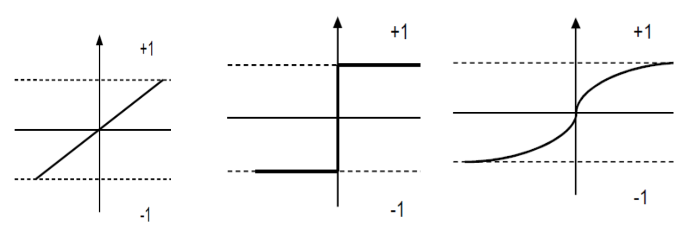


Figure 4.1 *Neural Network*

The transfer function

The weights and the input output function specified is responsible for the behavior of the ANN. There exist three major types of transfer function (1) Linear (or ramp) (2) Threshold and (3) Sigmoid as shown in the Figures 4.3 (a), (b), (c) respectively. The output is proportional to the total weighted output as far as linear transfer function is concerned. The output is set and depends on the value of the total input which may be greater than or less than some threshold value in the threshold transfer function. In sigmoid functions the output changes continuously but not linearly as the input changes. Sigmoid units have a better similarity to real neurons than the linear or threshold transfer functions but all three are considered to be rough approximations.



(a)Linear transfer function (b)Threshold transfer function (c)Sigmoid transfer function

4.2 Types of transfer functions

The neuron in the network acts as the processing element which carries out summation and the transfer function to convert input to output. The summation function calculates the signed weighted sum of all inputs at a given node. The total resulted input is allowed to pass through the transfer function or the activation function to generate output. The behavior of the network depends largely on the transfer function of the node. In a typical sigmoid function, the input (X) may be converted to the required output by the equation as found in most of the networks. F(x) =$\frac{1}{1+e^{-x}}$

4.1 Network Layers

Commonly the ANN consists of three groups/layers/units, where the layer of input is connected to the hidden layer and which in turn is connected to the layer of output as shown in the figure. The duty of the input layer is the raw data that is given to the network and the every hidden layer is determined by the function of the input layers and the weights on the connections between the input and the hidden layer. The behavior of the output depends on the hidden layers and the weights between the hidden and the output layers. The ANN structure can be single or multi-layer. As far as single layer is concerned all the layers are connected with one another which is the most general case and has more computing potential as compared to multilayered.

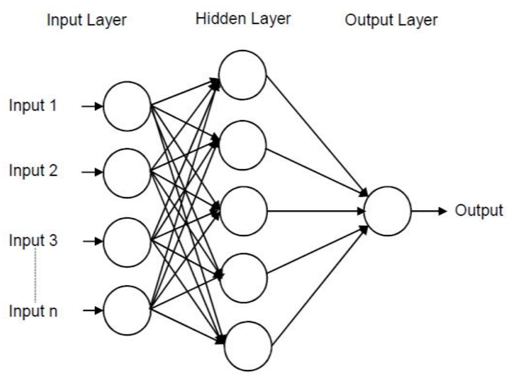


Figure 4.3 *Three layered simple feed forward neural network*

4.2 Architecture of neural networks

The architecture of the neural networks can be categorized as a) Feed-forward networks In the Feed-forward networks the signal is allowed to travel in one direction only i.e. from input to output. There is no feedback available which means the layer output has nil effect on the same layer. This is a straight forward network which relates the inputs and the outputs. They are mostly used in pattern recognition. It is also called as the bottom up or the top down b) Feedback networks In the Feedback networks the signals can travel in both directions by providing loop in the network. These are very powerful and are more complicated. They are dynamic with the state changing continuously till equilibrium is attained. They do not change and remain at the equilibrium till the input changes to get new stable point. They are also called as the interactive or recurrent.

4.3 The learning process

The training or the learning processes are nothing but the memorization of the pattern and the consequent response of the network. The knowledge is contained by the values of the connection weights and is possessed by the network. Changing the knowledge stored in the network as a function of experience means a rule of learning for changing values of weights. Complete information is saved in the weight matrix 'W' of a neural network. Learning is the evaluation of the weights. There are two types of neural networks learning:

1. Fixed network learning where the weights are not changed i.e. $dW / dt = 0$. Depending on the problem the weights are fixed in these networks.

2. Adaptive network learning can change their weights i.e. $dW / dt \neq 0$ Every learning methods used for adaptive neural networks can be classified into two major categories:I. Supervised learning In the Supervised learning uses external teacher which tell the output layer what its required response to the input signal is. The global information is needed for the learning process. Error correction, reinforcement and the stochastic are the examples of the supervised learning. The problem of the error convergence is the major issue in the supervised learning which is nothing but he minimization of the error between the desired and the calculated values. It is focused to determine a set of weights which minimizes the error. The common method is the least mean square (LSM). II. Unsupervised learning In the Unsupervised learning external teacher is not required and needs the local data. It s also called as the self-organized as itself organizes the presented data to the network and finds out the collective emerging property. Models of unsupervised learning are Hebbian and competitive learning. Normally, supervised learning is carried out off-line on the other hand unsupervised learning is carried out on-line.

4.4The back propagation (BP) algorithm

The i-m-n (i input neurons, h hidden neurons, and o output neurons) architecture of a back propagation neural network model as shown in Figure 4.4. The input layer gets the information from the outside sources and gives this to the network for processing. The information to the hidden layer is given by the input layer and carries out the processing and this processed information is given to the output layer and gives out the results. The inter connection weights modify the input signal called as weight factor W_{ij} that represents the connection of the first layer i^{th} node and the second layers j^{th} node. The sigmoidal function modifies the sum of the modified signals (f). On the same line the interconnection weight (W_{ij}) of output layers k^{th} node to hidden layer j^{th} node. The linear transfer function (f) modifies the sum of the modified signals and the output layer gives the output [199,200]. Sigmoid transfer function A bounded, monotonic, non-decreasing, S-shaped function provides a graded nonlinear response. It includes the logistic sigmoid function. $f(x)=\frac{1}{1+e^{-x}}$ Where x = input parameters taken as described above. In the present case batch mode type of supervised learning is used in which weights are adjusted with the help of delta rule algorithm by sending the complete sample of training to the network. At the time of training, the predicted output is compared with the preferred output, further calculating the mean square error. If the error is more than a set limiting value, it is back propagated, and weights are additional modified till the error or number of iterations is within a prescribed limit [201,202]. Mean square error, E p for pattern p is defined as $E\ p = \sum_{i=1}^{n} \frac{1}{2}\,(D_{pi} - O_{pi})^2$ Where, D_{pi} = target output, and O_{pi} = calculated output for the i^{th} pattern. Weight change at any time t, is given by $\Delta W(t)=-\eta E_p\ (t)+\alpha x \Delta W(t-1)$ H is the learning rate i.e. $0<\eta<1$ A is the momentum coefficient i.e. $0<\alpha<1$

4.5 Network parameters

The survey response for 24 items which is carried out in the industries is used to calculate the sustainability in these units. Three layered network is preferred with the input (i), a hidden layer and the output layer with single node. Outputs concerning the overall responses assessment of foundry industry as sustainability in the units are considered as the outputs. For the training and testing of the 199 survey data neural network with back-propagation module in the MATLAB is used. For better prediction, 70% (139) of data are taken for training set and 30% (60) are taken for testing set. The complete data are normalized in the 0-1 range to prevent the scaling effect of parameter values. Therefore, all the data (Xi) are converted to normalized values (Xnorm) as follows [203]. $X_{norm} = 0.8 \times \frac{X_i - X_{min}}{X_{max} - X_{min}} + 0.1$ where X_i is ith input or output variable. X_{min} and X_{max} are minimum and maximum value of variable X.

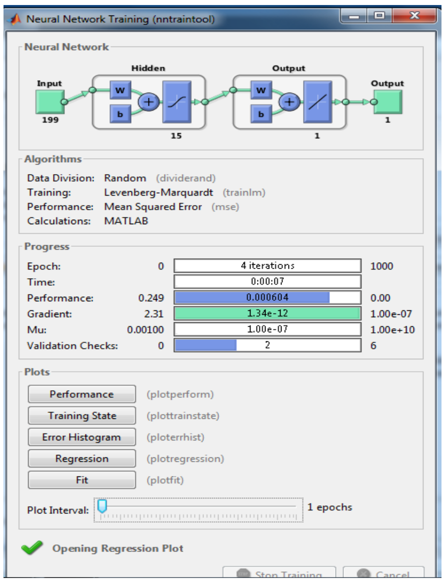


Figure 4.4 *Neural network training for output*

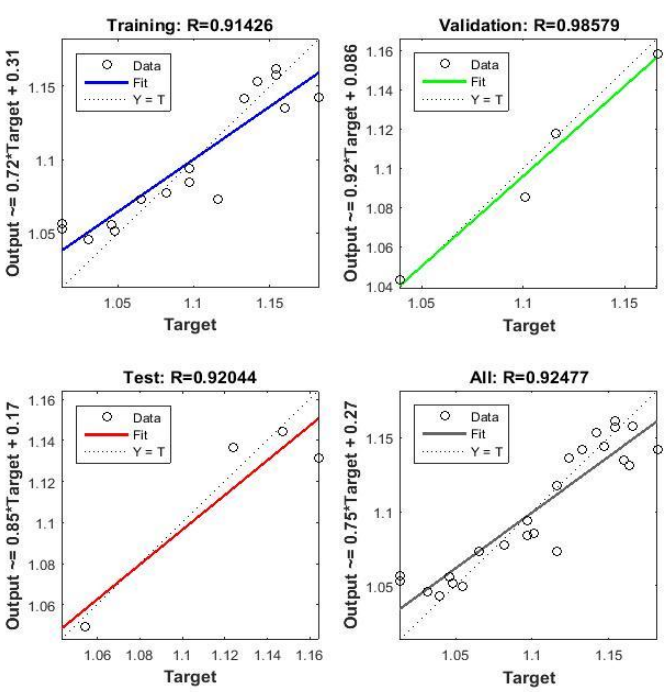


Figure 4.5 *Actual Vs. predicted of output*

For the training, number of trial were carried out by varying the number of hidden layers from 5 and increasing up to 20 and the mean square errors are checked for the training, validating and the testing. The statistical parameters like the mean square error (MSE), root mean square error (RMSE) and the correlation coefficient (R^2) of the training, validation and testing set of data is presented in the table. The hidden layer with 15 resulted in the lowest value of the MSE for all the parameters. Thus the configuration of 24-15-1 of neural network was used for the model.

Table: 4.1 *Neural network statistical parameters*

Sets	Hidden Layers	MSE	RMSE	R	R^2
Training	5	0.0045	0.0673	0.9210	0.8482
Validation		0.0180	0.1342	0.8810	0.7762
Testing		0.0029	0.0535	0.9580	0.9178
Training	6	0.0024	0.0485	0.9990	0.9980
Validation		0.0073	0.0853	0.8850	0.7832
Testing		0.0363	0.1905	0.4110	0.1689
Training	7	0.0045	0.0673	0.9330	0.8705
Validation		0.0077	0.0877	0.8770	0.7691
Testing		0.0145	0.1204	0.9130	0.8336
Training	8	0.0053	0.0729	0.9170	0.8409
Validation		0.0022	0.0468	0.9230	0.8519
Testing		0.0078	0.0883	0.9920	0.9841
Training	9	0.0029	0.0541	0.9930	0.9860
Validation		0.0229	0.1513	0.5370	0.2884
Testing		0.0073	0.0855	0.9560	0.9139
Training	10	0.0046	0.0675	0.9220	0.8501
Validation		0.0194	0.1393	0.8540	0.7293
Testing		0.0073	0.0857	0.9930	0.9860
Training	11	0.0045	0.0673	0.9300	0.8649
Validation		0.0054	0.0733	0.9050	0.8190
Testing		0.0071	0.0842	0.9900	0.9801
Training	12	0.0045	0.0673	0.9190	0.8446
Validation		0.0213	0.1459	0.7760	0.6022
Testing		0.0079	0.0889	0.8680	0.7534
Training	13	0.0045	0.0673	0.9230	0.8519
Validation		0.0314	0.1772	0.8860	0.7850
Testing		0.0092	0.0957	0.9920	0.9841
Training	14	0.0045	0.0673	0.9260	0.8575
Validation		0.0117	0.1082	0.9760	0.9526
Testing		0.0298	0.1726	0.1350	0.0182
Training	15	0.0023	0.0479	0.9990	0.9980
Validation		0.0419	0.2047	0.6590	0.4343
Testing		0.0034	0.0585	0.9810	0.9624
Training	16	0.0051	0.0717	0.9160	0.8391
Validation		0.0074	0.0861	0.9730	0.9467
Testing		0.0151	0.1229	0.7850	0.6162

Training	17	0.0045	0.0673	0.9270	0.8593
Validation		0.0203	0.1425	0.7020	0.4928
Testing		0.0122	0.1105	0.8860	0.7850
Training	18	0.0051	0.0717	0.9130	0.8336
Validation		0.0244	0.1562	0.8970	0.8046
Testing		0.0076	0.0870	0.9200	0.8464
Training	19	0.0079	0.0890	0.8720	0.7604
Validation		0.0043	0.0653	0.9660	0.9332
Testing		0.0185	0.1360	0.7810	0.6100
Training	20	0.0051	0.0717	0.9180	0.8427
Validation		0.0152	0.1233	0.8480	0.7191
Testing		0.0268	0.1637	0.8120	0.6593

5 VALIDATION OF THE MODEL

The obtained results of the neural network model are validated using the absolute difference in percentage (ADP). The absolute difference in percentage is the ratio of difference between the target values and the results obtained from the developed model to the target values. The values of the absolute difference in percentage show that the developed model is able of predicting the desired output reliably.

Table: 5.1 *Comparison of the target and predicted values*

Parameters	Target Values	Predicted Values	ADP
1	0.868342	0.830885	4%
2	0.876382	0.850284	3%
3	0.876382	0.848156	3%
4	0.873367	0.837836	4%
5	0.509548	0.463026	9%
6	0.857286	0.728829	15%
7	0.88005	0.701291	20%
8	0.520603	0.4926	5%
9	0.858291	0.864806	1%
10	0.505528	0.541247	7%
11	0.407035	0.425644	5%
12	0.882412	0.761299	14%
13	0.878392	0.954143	9%
14	0.501508	0.535406	7%
15	0.511558	0.5719	12%
16	0.868342	0.872226	0%
17	0.555779	0.570475	3%
18	0.553769	0.56953	3%
19	0.560804	0.572845	2%
20	0.891457	0.863158	3%
21	0.545729	0.61057	12%
22	0.858291	0.881839	3%
23	0.869347	0.835556	4%
24	0.878392	0.93471	6%

6 SENSITIVITY ANALYSIS

The impact on the output of a developed model by changing the input values is known as Sensitivity analysis. The neural network results are difficult to explain some times, thus the help of sensitivity analysis is required to explore the relation between the input and the output of the neural network model. It shows the contribution of the input to the desired output. Thus it can be summarized as the random variation of the input and noting the corresponding change in output. In this work the analysis was carried out to check parameters affecting the working environment. First the inputs were fixed at the actual values and the resulting output was measured. The sensitivity analysis was carried out by elimination the parameters one after the other and recording the corresponding change in the in output. The rank of the sensitivity of each input variable is calculated and presented in the table below.

Table: 5.2 *Sensitivity analysis with the developed model*

Parameters	Importance	Rank
13	0.644	1
9	0.560	2
6	0.548	3
22	0.528	4
1	0.492	5
24	0.482	6
12	0.422	7
15	0.419	8
17	0.365	9
11	0.337	10
21	0.323	11
20	0.320	12
4	0.302	13
2	0.301	14
18	0.299	15
10	0.273	16
23	0.272	17
8	0.264	18
19	0.248	19
7	0.246	20
3	0.224	21
5	0.206	22
14	0.197	23
16	0.000	24

From the results of the sensitivity analysis the ranking of the parameters rather the parameters to be addressed first is obtained. The top ten parameters are optimum utilization of power, high power factor should be maintained, proper means for maintaining the melting temperatures must be implemented, the overall energy consumption pattern should be kept minimum, the GHS emission should be reduce with proper means, the environment should not be disturbed and the admissible emission level must be maintained, the health and the safety of the workers should be maintained by providing the proper personal protective equipment's and lastly the work ethics should be followed to a larger extent.

7 CONCLUSION

This study has given a cataloguing and prediction model based on soft computing techniques (ANN) appropriate for examining foundry industry performance. The contribution of this chapter is to provide a logical integrated approach for modeling officers and workers opinion on foundry industry performance in the Indian industries. As energy is a sensitive issue in all kind of industrial setting, it is very essential to find a solution for energy conservation in industry. A work environment in foundry industry considered in this study is generally viewed as hazardous compared to other sectors due to use of high temperature melting furnace, unsafe and primitive tools and dust (fumes) produced during melting process. All of them increase the potential for inefficient performance of industry and hazard issue. It is obvious that a focused effort towards to make foundry industry sustainable is needed. It is found that from the survey that the manager, officer and workers have the opportunity as well as responsibility to encourage making industry economic, social and environmental friendly. In this study the impact of each factor of the valid instrument is measured through sensitivity analysis using artificial neural network (ANN). A model is developed for improving industry performance and section-wise perception for sustainable foundry industry has been identified so that policy formulation and implementation become easier. The study reveals that 24 factor for the outcome “Sustainability” (Economic, Environmental and Social) are most sensitive factors to be dealt carefully. The economic, environmental and social losses are occurs due to lack of knowledge, incorrect procedures, technical expertise and inability of the internal actors to implement changes. The workers are often overexposed to inefficient performance of industry and occupational hazard because they are concentrated in very high-risk section in industry and they know little or nothing about responsibility, rights, and duties and about the use of efficient methods to prevent losses. Therefore, cultural adaption of Sustainable foundry industry measure must be promoted through commitment by both employers and employees.

REFERENCES

[1] AGARWAL, A.R., SHANKAR, R. AND TIWARI. M.K. (2007). MODELING AGILITY OF

[2] SUPPLY CHAIN. *INDUSTRIAL MARKETING MANAGEMENT 36(4)*, 443-457.

[3] KANO, N., SERAKU, N.K., TAKAHASHI, F. AND TSUJI, S. (1984). ATTRACTIVE

[4] QUALITY AND MUST BE QUALITY. *QUALITY 14(2)*, 39-48.

[5] Lee, T.W. (1988). How job dissatisfaction leads to turnover. *Journal of Businessand Psychology 2(3)*, 263-271.

[6] Tsai, K.H. (2000). Relationships among organization commitment, job

[7] satisfaction and turnover intention: A meta-analysis. *Journal of Chinese*

[8] *Management Review 3(4)*, 33-49.

[9] Williams, M.L. (1995). Antecedents of employee benefit level satisfaction.

[10] *Journal of Management 21(6)*, 1097-1128.

[11] Keller, S.B. (2002). Internal relationship marketing: A key to enhanced

[12] Supply chain relationships. *International Journal of Physical Distribution*

[13] *and Logistics Management 32(8)*, 649-668.

[14] Siengthai, S. and Bechter, C. (2005). Human resource management in

[15] Thailand: A strategic transition for firm competitiveness. *Research and*

[16] *Practice in HumanResource Management 13(1)*, 18-29.

[17] McCloskey, E. (2008). The health and safety of young people at work: a

[18] Canadian perspective. *International Journal of Workplace Health Management1(1),* 41-49.

[19] McDermott, L.C. and Emerson, M. (1991). Quality and service for internal customer. *Training and Development Journal 45(1)*, 61-64.

[20] Chaston, I. (1994). Internal customer management and service gaps

[21] within the UK manufacturing sector. *International Journal of Operations and Production Management 14(9)*, 45-56.

[22] Gremler, D.D., Bitner, M.J. and Evans, K.R. (1994). The internal service

[23] encounter. *International Journal of Service Industry Management 5(2)*, 9-19.

[24] Marshall, G.W., Baker, J. and Finn, D.W. (1998). Exploring internal

[25] Customer service quality. *Journal of Business and Industrial Marketing 13(4/5)*, 381-392.

[26] Patnaik, B., Beriha, G.S., Singh, N. and Mahapatra, S.S., Organizational

[27] learning in educational settings (Technical): An Indian perspective.

[28] Higher Education, Springer Publication.

[29] Beriha, G.S., Patnaik, B., Mahapatra, S.S., Sahu, R. and Deshpande, S.,

[30] Assessing influence of social marketing on occupational health and

[31] safety: Quality function deployment and interpretive structural modelling

[32] approach. International Journal of Nonprofit and Voluntary Sector

[33] Marketing, Interscience, Wiley Publication.

[34] [15]Beriha, G.S., Patnaik, B. and Mahapatra, S.S., A neural network approach

[35] For assessment of occupational health practices. Safety Science, Elsevier

[36] Publication.

[37] Datta. S., Beriha, G.S., Patnaik, B. and Mahapatra, S.S. (2009). Use of

[38] COPRAS-G method for supervisor selection: A multi-criteria decision

[39] making (MCDM) approach. International Journal of Vocational and

[40] Technical Education 1(1), 007-013.

[41] Satapathy, S., Patel, S.K., Biswas, A., Mahapatra, S.S. and Beriha, G.S. (2010). A QFD and ISM approach to a service industry. International

[42] Journal of Advanced Manufacturing Systems 1(2), 191-196.

[43] A. F. Murray, *Applications of Neural Networks*, Boston: Kluwer Academic, 1995.

[44] Z. H. Zhou, Y. Jiang, Y. B. Yang, and S.F. Chen, “Extracting neural

[45] networks from trained neural network Ensembles”, *AI Communications*,

[46] Vol. 16 No.1, pp. 3-15, 2003.

[47] Anuwat Pansuwan March 18 - 20, 2009, Hong Kong Temperature

[48] Estimation of Liquid Steel in Induction Furnace”, Proceedings of the

[49] International Multi Conference of Engineers and Computer Scientists 2009 Vol II IMECS 2009

[50] Davis F. and M. Decrop, 1958 “Influence of Blast Input, Coke Size and

[51] Melting Coke Ratios on Cupola Performance", Foundry Trade Journal, pp. 319-325. [5] Pehle R. D., (1963). "Thermo-chemical Model of
[52] Computer Prediction of Cupola Performance", AFS Transactions, Vol.
[53] 71, pp. 580-587
[54] E. Kardas, December 2012, "Evaluation of Efficiency of Working Time
[55] of Equip ment in Blast Furnace Department", Journal of Achievements in
[56] Materials and Manufacturing Engineering Volume 55 Issue 2 Pages 876- 880
[57] Pritibhushan Sinha and SubhashSaha, Chandra "An Optimum Design of
[58] the Lining of a Medium Frequency Induction Melting Furnace",
[59] International Transactions in Operational Research Vol 5 No. 4, Pages 255-259
[60] Price, L. and McKane, A., (2009). Industrial Energy Efficiency and
[61] Climate Change Mitigation: Policies and Measures to Realize the
[62] Potential in the Industrial Sector, Prepared in support of the UN.
[63] S.K. Dutta, A.B. Lele and N.K. Pancholi, October 2004 "Studies on
[64] Direct S.K. Dutta, A.B. Lele and N.K. Pancholi, "Studies on Direct Inst.
[65] Met.Vol.57, No. 5 Pages 467- 473
[66] Singh R., Patvardhan C., Jain R. K. and A. Kumar,2000 "Effect of Air -
[67] Preheating and Excess Air on the Performance of LDO Fired Rotary
[68] Furnace" Indian Foundry Journal, Vol. 46, No. 11, pp. 26-32.
[69] Vasin Kiattikomo, Arun Chatterjee, Joseph E. Hummer, and Mary Sue
[70] Younger, 2008 "Planning Level Regression Models for Crash Prediction on Interchange and Non-Interchange Segments of Urban Freeways,"
[71] Journal of Transportation Engineering, 134 (3).
[72] Veleva, Vesela, and Michael Ellenbecker. "Indicators of sustainable
[73] production: framework and methodology."Journal of Cleaner Production 9, no. 6 (2001): 519-549.