Implementation of fuzzy technique in the prediction of sample demands for industrial lubricants

Rajkumar Sharma, Piyush Singhal

Abstract: ***In this paper, a case of prediction of sample demands for industrial lubricants has been presented. We have observed that the demand for most of the industrial lubricants depends on three main factors i.e. quality, cost, and delivery time. These factors are studied and compared with other competitors dealing in similar nature of products. The quality is mapped with three fuzzy parameters viz. inferior, alike, and superior. The cost is linked with three linguistic variables viz. low, identical & high. Similarly, delivery time is also associated with three sub-parameters viz. short, equal and long. First, the raw data of demand for 12 number of random samples are collected from supply chain executives of an automotive and industrial lubricant manufacturing company. Thereafter, the membership functions for the causal factors and demand are built on the basis of comparative analysis and collected data. At last, a fuzzy- inference demand model with rule base is constructed. Finally, the demands are predicted by the skilled fuzzy model. Predicted data is compared with the raw data and absolute errors are being calculated. The result shows predictions made by the fuzzy-inference demand model are in tune with the actual demands of industrial lubricants. Thus, the built fuzzy model can be utilized and generalized for effective demand forecasting for industrial products***

Index Terms: Demand, Forecasting, Fuzzy logic, Membership function, Prediction.

I. INTRODUCTION & LITERATURE REVIEW

The supply chains consist of consumers, distributors, manufacturers, and, suppliers. The demand at the consumer node is considered one of the major supply chain disruptions due to its random nature. The management of inventory, the supply of raw material, production, etc. can be improved if true and exact demands are identified in advance. That's why; demand forecast is very important to research area these days. Accurate demand prediction in each and every field is getting value, as it drastically affects the profits, return and growth of supply networks. Therefore, the application of artificial intelligence methods like a neural network, fuzzy logic, and genetic algorithm etc. has become very popular in the field of demand management. During the literature review, we observed that a fuzzy model for the forecasting of the demand for power in the Jordan region has been developed [1]. Overview of fuzzy set theory with two numerical examples was discussed by X .W. Ma et al. [2] to solve the problems of power systems. The problems of risk in the construction industry were addressed by using fuzzy terms [3]. Application of fuzzy logic and neural network in the prediction of energy price was shown in the Ontario region [4]. Optimization of the supply chain by handling the uncertainty i prices of the product as fuzzy variables have also been worked out [5]. The forecasting of the load for Neyveli Thermal Power Station in India was to be had, using two input parameters i.e. time and temperature with fuzzy logic again [6]. These both parameters are the subset of seven parameters(i.e. time, geographical location, temperature, climate), population and industrialization) used in [1]. Linguistic terms for the coordination in supply chains were defined [7]. Use of fuzzy in the optimization of the automobile supply chain was exercised and the effectiveness of fuzzy under uncertainty is demonstrated [8]. Mark ko et al. [9] addressed supply chain problems like demand forecasting, bullwhip effect, inventory management and many more by presenting a review of soft computing methods like a neural network, genetic algorithm and fuzzy logic etc. in the field of supply chain management. Further, the fuzzy model for the assessment of risk in the construction industry using trapezoidal fuzzy member was designed [10]. Xiaojun Wang et al. [11] proposed a technique to asses food safety risk in the production process of the food supply chain. In parallel, a case study of National Electric Power Company(NEPCO) in Jordan for predicting the short term loads by using some different parameters like forecasted temperature, and, consumption of power & temperature for last day and last week is presented[12]. This case study compared the predicted loads with the actual loads and proved that results obtained by fuzzy methods are more accurate than conventional methods. Thereafter, Darshan Kumar et al. [13] built a fuzzy logic based decision support system to evaluate the selection of suppliers in the supply chain based on the effect of quality, cost & time. At last, few papers in the literature dealing on the uncertainty of return product refurbishment based on fuzzy logic were also seen [14]. The paper by Darshan Kumar et al. [13] motivated the author to use fuzzy logic in the forecasting of demands of engine oil for automotive and industrial lubricant manufacturing company. The rest of the paper is organized as follows: Section two provides a general description of the development of the system. Methodology for building membership functions is described in section three. Section 4 presents the fuzzy-inference demand model.

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Simulated results are discussed in section 5. Finally, the paper concludes in section 6.

II. DEVELOPMENT OF THE SYSTEM

The quality, cost and delivery time are considered independent (input) variables on which demand for engine oil depends. The demand for engine oil is mapped with the dependent(output) variable. Now, it is worthy to define the following terms.

A. Quality outcome

The quality outcome is the measure of quality on different parameters like lubricating power, its viscosity, to absorb external contamination particle etc. when compared with other competitor's product quality, working in the same field. It can be measured in percentage (%). In a general way, the quality outcome can be considered superior if its value is more than 65 % and inferior if its value is less than 35%. For the range [45 to 55] it can be termed alike in building the fuzzy logic. The demand for lubricant is directly proportional to quality outcome i.e. if the quality outcome is superior, then the demand of the lubricant will be high in the market. So, we logically assume that the range [0, 35] indicates inferior quality, [45, 55] indicates alike, and [65,100] represents superior quality as compared to other competitors quality dealing in similar nature of products.

B. Cost-outcome

Cost-outcome is the measure of the total life-cycle cost of the lubricant when compared with other competitor's total cost, working in the same field. It can also be measured in percentage (%). In a general way, cost outcome can be considered high if its value is more than 65 % and low if its value is less than 35%. For the range [45 to 55%] it can be termed identical in building the fuzzy logic. The demand for lubricant is inversely proportional to cost outcome i.e. if cost outcome is low then demand of the lubricant will be high in the market. So, we again logically assume that the range [0, 35] indicates low cost, [45, 55] indicates identical cost, and [65,100] represents high cost as compared to other competitors cost dealing in similar nature of products.

C. Delivery time outcome

Delivery time outcome is the measure of time taken for delivery of the lubricant in right quantities at the right place, just after the buyer has put an order, when compared with other competitor's delivery time, working in the same field. It can also be measured in percentage (%). In a general way, delivery time outcome can be considered long if its value is more than 65 % and short if its value is less than 35%. For the range [45 to 55%] it can be termed equal in building the fuzzy logic. The demand for lubricant is inversely proportional to cost outcome i.e. if cost outcome is low then demand of lubricant will be high in the market. The range [0, 35] indicates short delivery time, [45,55] indicates identical delivery time, and [65,100] represents high delivery time as compared to other competitors delivery time dealing in similar nature of products.

For picking the significant dynamics of the system, these outcomes are associated with suitable linguistic terms as shown in Table I. The linguistic terms are decided after comparing the outcome of independent variables with respect to other competitors dealing with similar nature of products.

Table I. Input Variables mapping with linguistic terms.

Independent variable	linguistic term 1	linguistic terms 2	linguistic terms 3
Quality outcome	Inferior	Alike	Superior
Cost-outcome	Low	Identical	High
Delivery time outcome	Short	Equal	Long

The demands for industrial lubricants are associated with seven linguistic variables as shown in Table II. The reason for more number of linguistic variable assignments at this stage will result in creating the effective rule base at the later stage.

Table II. Output Variable mapping with linguistic terms.

Linguistic term	Dependent variable	Abbreviation
Linguistic term 1	Very very low	VVL
Linguistic term 2	Very low	VL
Linguistic term 3	Low	L
Linguistic term 4	Normal	N
Linguistic term 5	High	H
Linguistic term 6	Very High	VH
Linguistic term 7	Very very high	VVH

III. MEMBERSHIP FUNCTIONS

The membership functions for all the three manipulated and one target variables are prepared using MATLAB fuzzy toolbox. The membership functions for the quality outcome with linguistic terms Inferior, Alike and Superior are shown in Fig. 1(a). The range for the quality outcome is considered between [0, 100]. It is to be noted here that quality outcome may be associated with more than three linguistic variables like VVI (very very inferior), VI (very inferior), I (inferior), A (alike), G (good), VG (very good), E (excellent) etc. It will require more memory space and computing power with little improvement in accuracy. Hence we select only three linguistic variables in the preliminary stage of system design and reject other unwanted linguistic terms for simplicity.

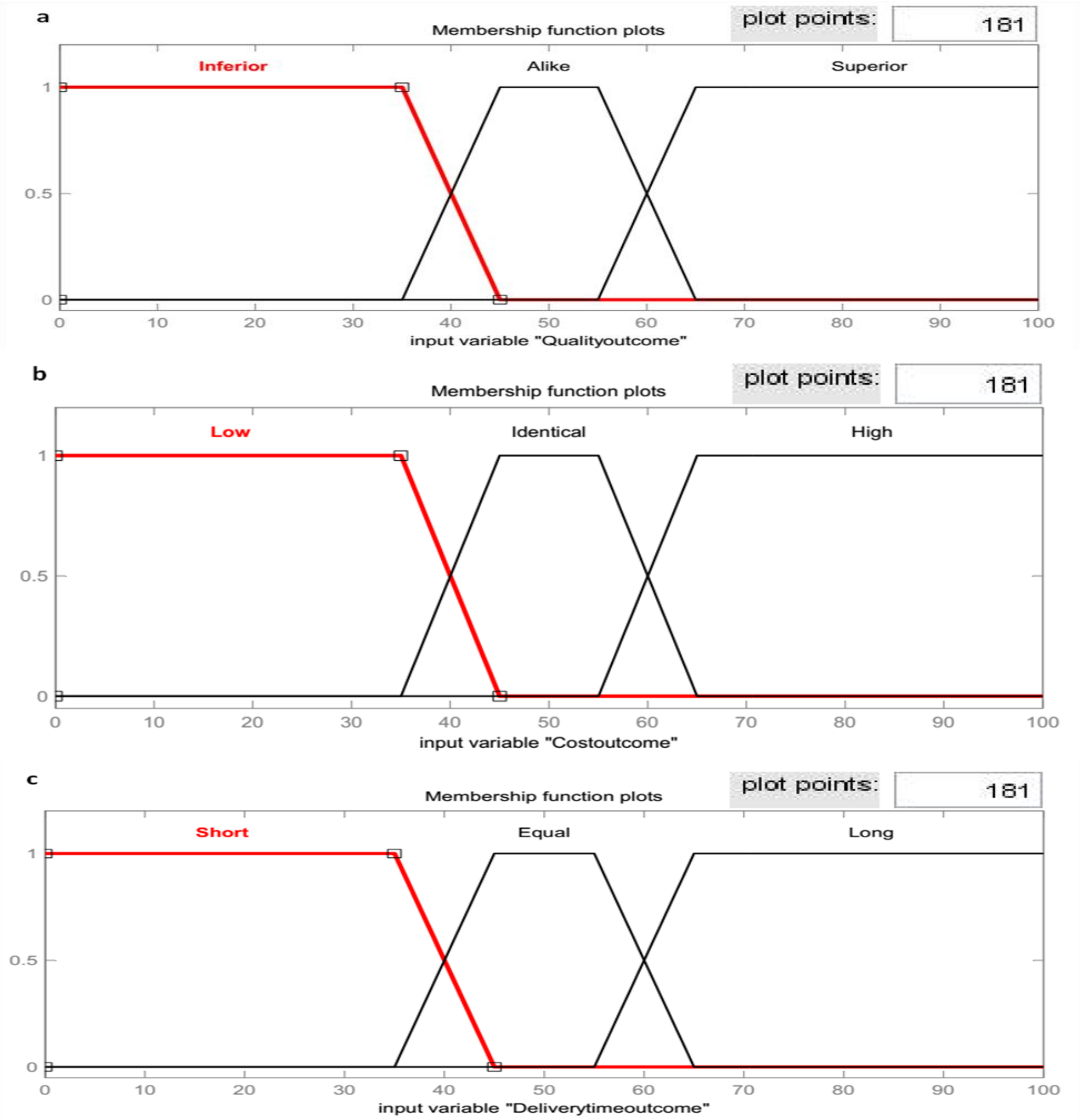

Fig. 1.(a)Membership function for the quality outcome; (b) Membership function for cost outcome; (c) Membership function for delivery time outcome;

The shape of the membership function is selected trapezoidal in nature as this shape is capable to provide good results as seen in the literature [1,2,6]. The degree of membership in fuzzy implementation is always by default between [0, 1]. The membership functions for cost outcome with linguistic terms Low, Identical and High are shown in Fig. 1(b). The range for cost outcome is considered between [0, 100]. Similarly, the membership functions for delivery time outcome with linguistic terms Short; Equal and Long are shown in Fig. 1(c). The range for delivery time outcome is considered between [0, 100]. The raw data of demand for engine oil for 12 number of samples are displayed in Table III.

Table III. Demand data of engine oil.

Sample No.	Demand
1	128
2	104
3	112
4	91
5	132
6	124
7	120
8	96
9	80
10	129
11	156
12	76

Hence, the membership functions for demand with linguistic terms VVL(Very very low), VL(Very low), L(Low), N(Normal), H(High), VH(Very high), VVH(Very very high) are built as shown in Fig. 2. The range for demand outcome is seen between [76, 156] for random sample data. The range for demand in the fuzzy model is kept between [65 170] for the better covering of lower and upper boundaries. The membership functions for demand are shown in Fig. 2.

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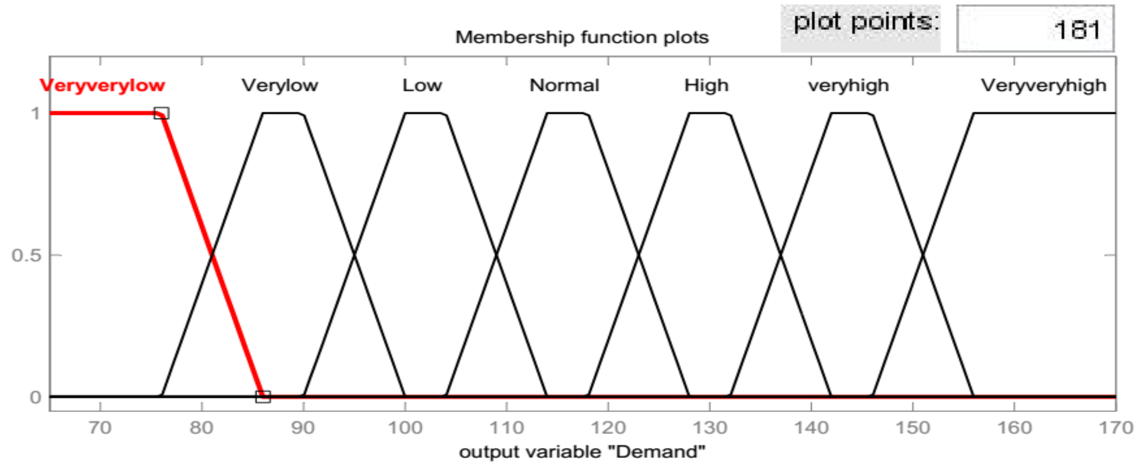

Fig. 2. Membership function for output variable(demand)

I. Fuzzy-inference Demand model

Fuzzy-inference demand model using the Mamdani method available in MATLAB Simulink is created as shown in Fig. 3. The model captures the three input and predicts one output i.e. the demand in our case.

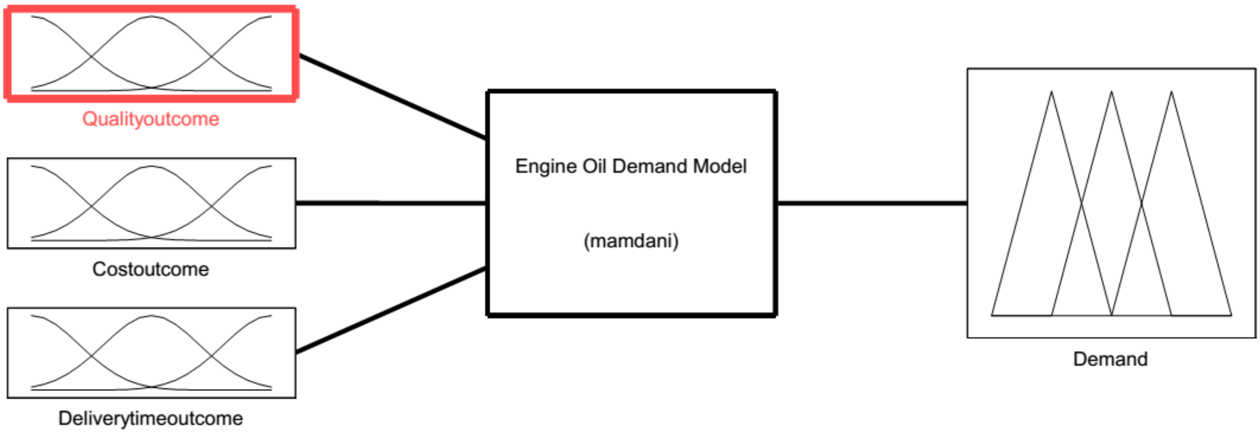

Fig. 3. Fuzzy-inference demand model.

A total of 27 (3*3*3) rules are made to capture the dynamics of the system. The model of the system fires these rules to predict the demands of industrial lubricant. Some examples of rules to make the process clear are shown in Table IV. Membership functions convert the variables into fuzzy variables. Aggregation is performed using the max function. The fuzzy output is calculated by firing the rules. Defuzzification is carried out through the centroid method.

Table IV. Fuzzy rule base

Rule No.	If the quality outcome is	And if cost outcome is	And if delivery time outcome is	Then the demand will be
1	Superior	Low	Short	Very very high
2	Superior	Identical	Short	Very high
3	Inferior	Low	Short	High
4	Alike	Identical	Equal	Normal
5	Superior	High	Long	Low
6	Alike	High	Long	Very low
7	Inferior	High	Long	Very very low

I. Simulated results & discussion

Some results of predicted demands by the fuzzy-inference model for different fuzzy combinations of quality, cost and delivery time outcome are displayed in Table V. From the Table V, it is quite clear that the relative error lies in the range [.008, .091]. Fig 4 depicts the output predicted by the model at a certain input [50 50 50] after firing 27 rules, made at the time of development of the fuzzy-inference model in section IV. A MATLAB code is prepared to analyze the relative error. A graph between sample number and relative error is plotted as shown in Fig. 5(a).The minimum and maximum error are found to be 0.008 and 0.091 for sample number 6 & 5 respectively. Fig. 5(b) shows the tuning between predicted and target demand.

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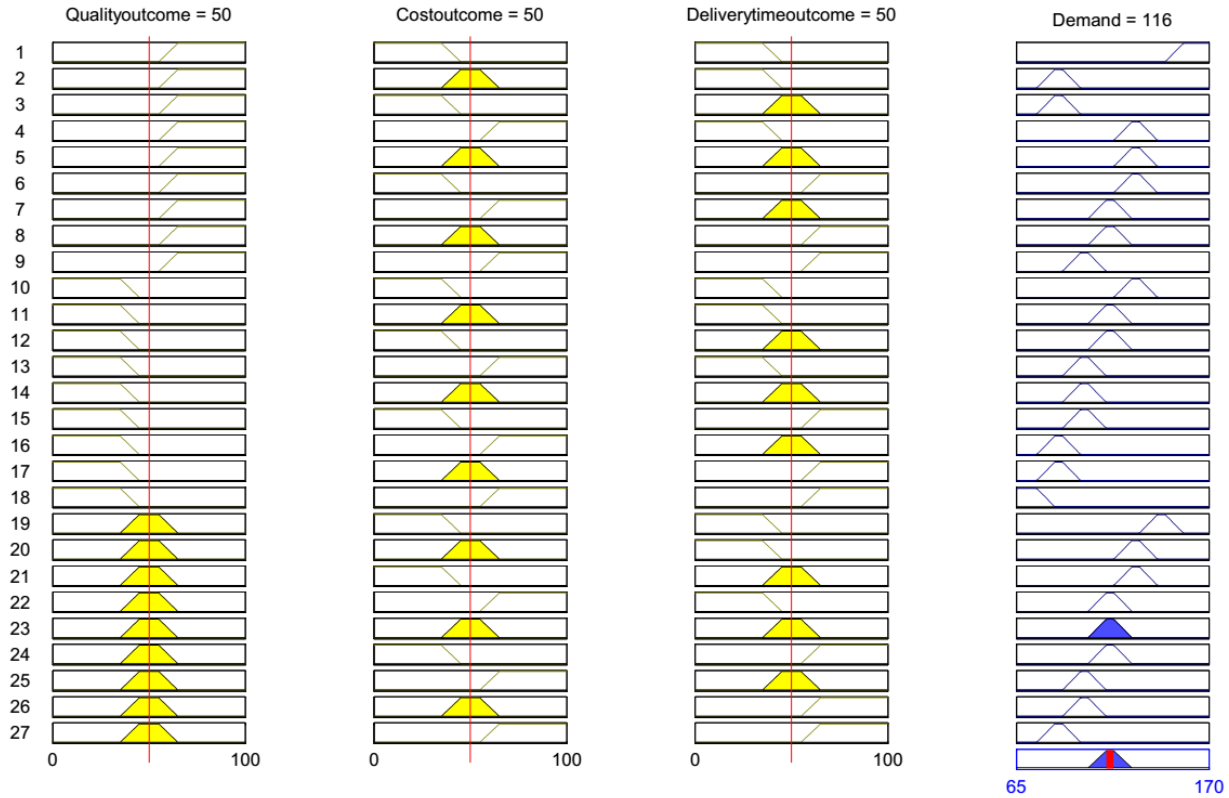

Fig. 4. Prediction of demand at a certain input(50 50 50]

Table V. Predicted demands with the relative errors between predicted and target data.

Sample No.	Quality outcome	Cost-outcome	Delivery time outcome	Predicted demand	Target demand	Relative error
1	100	100	0	130	128	0.016
2	0	100	0	102	104	0.019
3	100	100	50	116	112	0.036
4	0	100	50	88	91	0.033
5	50	0	0	144	132	0.091
6	60	47	47	123	124	0.008
7	50	50	50	116	120	0.033
8	40	50	70	95	96	0.010
9	40	80	80	81	80	0.013
10	7	37	7	127	129	0.016
11	100	0	0	161	156	0.032
12	0	100	100	73	76	0.039

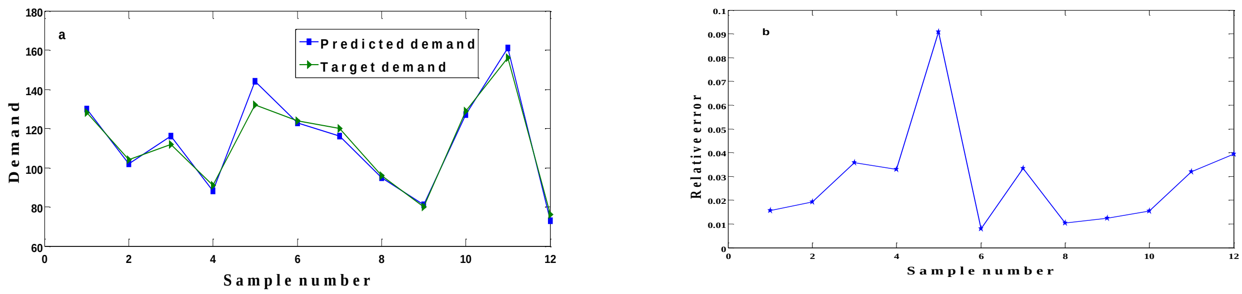

Fig. 5. (a)Tuning between predicted and targeted demand; (b) Relative error vs sample number

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I. CONCLUSION AND FUTURE SCOPE

The small absolute error indicates tuning between predicted and target demand. Tuning confirms that the designed fuzzy-inference model has picked the significant dynamics of the demand for industrial lubricants. The predictions made by fuzzy demand model are found approximately similar to the actual demands provided by supply chain executives of automotive and industrial lubricant manufacturing company for random sample data. Thus, it is concluded that the built fuzzy demand model can be utilized for accurate & precise future demand predictions for industrial lubricants. This model may provide better results if a large amount of historical data of random demand is made available. Some more input parameters, which affect the demand like delay and uncertainties in the production, transportation and, in the supply of raw material, may also be incorporated in the future in order to increase the accuracy and performance of the demand model for industrial lubricants. This model can also be generalized for other products by minor modification in changing the variables as per system requirement.

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Rajkumar Sharma is working as an Assistant Professor in the Department of Mechanical Engineering at GLA University Mathura. His research interest is in the area of Industrial Engineering. He has completed his graduation in first division from NIT Raipur(Chhattisgarh) and post-graduation M.Tech.(Design Engg.) with honors from GLA University Mathura. Currently, he is pursuing his Ph.D. in the area of supply chain management from GLA University Mathura. He has published around 15 peer-reviewed research papers in renowned conferences held at IIT's & IIM's till date. He is also an active member of the Alumni Association of GLA University. He has been awarded LEAN SIX SIGMA YELLOW BELT from Ministry of Micro, small & medium enterprises. He is also having online certification from NPTEL and also awarded with an online digital badge by AUTHORAID (INASP Moodle) with a certificate of merit available at http://moodle.inasp.info/badges/badge.php?hash=1ae69d27e7267d1f528d8696dd637a7016b20147. Apart from that many students have completed and some are still pursuing their B.Tech / M.Tech. project research work under his guidance and supervision.

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