IDENTIFICATION OF MAJOR LEAN WASTE AND ITS CONTRIBUTING FACTORS USING THE FUZZY ANALYTICAL HIERARCHY PROCESS

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ABSTRACT

Lean refers to the reduction of non-value added activities in industries. It focuses on seven types of lean waste. The significant challenge is to identify and reduce the major lean waste. With this objective, a survey was conducted in an international exhibition in India using a questionnaire. The collected data were analyzed using Analytic Hierarchy Process (AHP) software template to check consistency. Finding consistent results obtained in AHP satisfactory, ranking was carried out to find the major lean waste using fuzzy AHP. After the identification of the major lean waste, the major contributing factors for the waste were ranked using the Binary Logistic Regression (BLR). These contributing factors were further investigated for the waste elimination in the automobile component manufacturing industries.

Keywords: lean systems; analytic hierarchy process; fuzzy AHP; binary logistic regression.

IDENTIFICATION DES PRINCIPALES SOURCES DE GASPILLAGE ET SES FACTEURS CONTRIBUTIFS UTILISANT LE PROCÉDÉ DE L'ANALYSE HIÉRARCHIQUE FLOUE

RÉSUMÉ

La production au plus juste (lean) réfère à la réduction des activités à non valeurs ajoutées dans les industries. Elle se concentre sur sept types de gaspillage. Le défi important est d'identifier et de réduire les principales sources de gaspillage. Avec cet objectif en tête, on a mené un sondage par questionnaire dans une exposition internationale en Inde. Les données colligées ont été analysées au moyen du logiciel de méthodologie du procédé d'analyse hiérarchique (PAH) pour vérifier la consistance. Les résultats obtenus étant conformes au procédé d'analyse hiérarchique, le classement a été réalisé dans le but de trouver les principales sources de gaspillage en utilisant le procédé de l'analyse hiérarchique floue. Suite à l'identification des principales sources de gaspillage, les facteurs contributifs principaux ont été classés en utilisant la régression logistique binaire. Ces facteurs ont été étudiés plus en profondeur pour éliminer le gaspillage dans les industries manufacturières de composants automobiles.

Mots-clés : système d'élimination de gaspillage (lean); procédé d'analyse hiérarchique; procédé d'analyse hiérarchique floue; régression logistique binaire.

1. INTRODUCTION

Lean production is a method for the elimination of waste occurring in the manufacturing process. Lean means creation of value addition for customers with limited resources. Lean organization understands the customer value and focuses its key process for continuous increase in value. Lean transformation is used to characterize a company mainly from traditional thinking to lean thinking. Lean refers to the process that eliminates non-value added activities. The ultimate goal is to provide perfect value to the customer to enable production process with zero waste. Khalil et al. [1] started to analyze the existing situation of waste elimination through Wastes Relations Matrix (WRM). Elimination of lean waste helps reduction of manual effort, minimizes space requirements, reduces capital and production time and eventually proves cost effective. Most of the previous researchers focus on lean tools rather than on lean waste. This has given rise to the need for finding the major lean waste out of seven types of waste.The primary objective of this work is to identify the major lean waste in automobile component manufacturing industries using Fuzzy AHP. Saaty's [2] theory states fuzzy AHP showing relatively adequate description compared to the traditional AHP methods, wherein fuzziness and vagueness existing in many decision-making problems contribute to imprecise judgments of decision makers as stated in [3]. The secondary objective of this work is to determine the major contributing factors for the major lean waste using BLR. Basu et al. [4] used a constrained form of BLR for diagnosis of such problems. These two objectives are investigated to identify and suggest the major lean waste using Fuzzy AHP and also to determine the major contributing factors for the lean waste using BLR.

2. LITERATURE REVIEW

Lean manufacturing is a management philosophy parented by Toyota Motor Company. The main principles of lean manufacturing have been derived from the Toyota Production System (TPS). The aim of lean production is to reduce the seven cardinal lean wastes. Ahmed and Hoda [5] have carried out a case study in which bottlenecks were identified. The Lean Kaizen technique was used to remove the bottlenecks through reduction in cycle time, increasing productivity and eliminating lean waste. Koukoulaki [6] has stated that lean production can have combined effects based on the management style of the firms. Fullerton et al. [7] state that lean production is conceptually multifaceted, with its philosophical characteristics that are often difficult to measure directly. Yanga et al. [8] state waiting as the most common non-value adding activity. Demeter and Matyusz [9] have concentrated on improvement of inventory turnover performance through the use of lean practices. Firms making extensive application of lean practices had higher inventory turnover. Arunagiri and Gnanavelbabu [10] focus mainly on the various process methodologies that could reduce delay in the manufacturing process leading to productivity improvement. Powell et al. [11] have focussed on production section and created a state map for the future to suggest ways to reduce lead-time and increase productivity. Hofer et al. [12] stated that the effect of lean production on financial performance is partial mediation through inventory leanness. There is strong evidence for lean practices yielding larger performance benefits. Ringena et al. [13] demonstrated the Value Stream Mapping (VSM) technique and discussed the application of lean systems initiative on a product as VSM is involved in all the process steps. This visual tool helps identification of the hidden waste and sources of waste. Natasya et al. [14] state that the conceptual model for leanness measurement had been developed and designed at two levels namely, the dimensions and the factors. The model also indicates the relationship between lean dimensions in the manufacturing systems and eight types of waste. Krishnan and Parveen [15] studied and compared the various lean tools used and adopted in the manufacturing and the service sectors. Bruun and Mefford [16] provided a background in lean manufacturing and presented an overview of manufacturing wastes. The introduction of lean tools and techniques is useful in transforming a company into a high performing lean enterprise. Arunagiri and Gnanavelbabu [17] dealt with the identification of major lean production waste in

Table 1. Seven types of waste and its examples.

Type of waste	Definition	Examples
Overproduction (OPN)	Parts are manufactured without any new order or demand from customer [18]. OPN leads to excessive work in process stocks [19].	Large batch size, unstable schedule, unbalanced cells, inaccurate information on demand.
Defects (DES)	Production with incorrect specifications, physical defects leading to increase in cost [18].	Inadequate training, skill shortage, operator error, excessive stock.
Inventory (INY)	Storage of products with no orders on hand [18].	Excess inventory, large batch size, long change over time.
Transportation (TPN)	Movement of materials that do not add any value to the product [18].	Poor layout, large batch size, multiple storage locations.
Waiting (WTG)	Idle time for machines or workers due to bottlenecks or ill planned production flow [18].	Long changeover, unreliable process, time required to perform rework.
Motion (MON)	Unnecessary motions of workers, which divert them from actual processing work [18]. Motion involves poor ergonomics of production [20].	Poor layout, poor method design, large batch size, poor workplace organization.
Overprocessing (OPG)	Unintentionally conduct of more processing work than warranted by customer requirement [18].	No standardization of ideal techniques, unclear specification or quality acceptance standards.

automobile industries, using the weighted average method. Most of the previous researchers focus on lean kaizen, VSM, lean tools, effects of lean, inventory leanness and delay analysis. There is no study available in the prioritization of lean waste using the Multi criteria decision making process. The major lean waste is determined for filling this gap using Fuzzy AHP. The major contributing factors are identified using BLR.

3. MAJOR LEAN WASTE AND EXAMPLES

The seven types of lean waste have been identified as part of the Toyota production System. The list has since been modified and expanded with the addition of various practices of lean system. Each lean waste is defined with the relevant examples as stated in Table 1.

4. METHODOLOGY

The step by step methodology followed for identification of the major waste and its contributing factors are shown in Fig. 1. The tools used for this research are AHP, Fuzzy AHP and BLR.

4.1. Conventional AHP

AHP is one of the methods for ranking alternatives and selecting the best one when the decision maker has multiple options. In AHP, preferences between alternatives are determined through making pairwise comparisons as stated in [21]. The crux of AHP is the determination of the relative weights to rank the decision alternatives. Assuming n criteria at a given hierarchy, the procedure establishes a $n \times n$ pairwise comparison matrix, that reflects the decision maker's judgment on the relative importance of the different criteria. Pairwise comparison is made such that any criterion in a row i ($i = 1, 2, 3, \ldots, n$) is ranked relative to each of the other criteria represented by the n columns. The intermediate values between 1 and 9 are interpreted

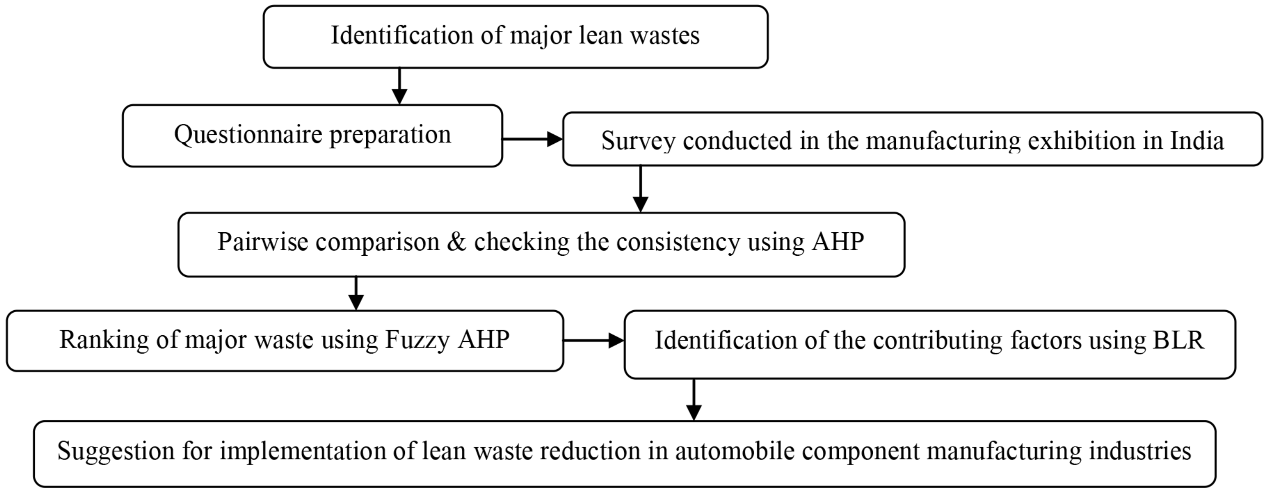

Fig. 1. Scheme of the research.

correspondingly. The mathematical results of attributes are given to the decision maker to assign relative ranks according to a predefined scale. Acceptability of an alternative is evaluated in terms of Consistency Ratio (CR) (CR = Consistency index/Mean random consistency index). Rao Tummala and Ling [22] stated that the CR assesses the overall consistency of all the pairwise comparison judgements given by the decision makers in the form of pairwise comparison judgement matrices.

4.2. Fuzzy AHP

There is extensive literature review that addresses the situations where the comparison ratios are not produce the precise judgments as stated in [23]. Humans fail to make quantitative predictions, whereas they are comparatively efficient in qualitative forecasting as stated in [24]. Shaw et al. [25] proposed an integrated approach for selecting the right supplier in the supply chain management using two techniques. The techniques are fuzzy-AHP and fuzzy multi-objective linear programming. Saaty's theory provides evidence for relatively satisfactory results for fuzzy AHP when compared to the traditional AHP methods. The detailed procedure for fuzzy AHP methodology is explained along with numerical illustrations in Section 5.2.

4.3. Binary Logistics Regression (BLR)

BLR is a method of choice when the dependent variable is binary. It explores the relative influence of continuous and categorical independent variables on the dependent variable for assessment of their various effects between the independent variables. In BLR, the values should be in binary either 1 or 0 for the sub factors. These binary values are considered in the mathematical calculations using BLR algorithm.

5. NUMERICAL ILLUSTRATIONS

5.1. Data Collection and Consistency Check Using AHP

Data collection was carried out using the questionnaire prepared based on the seven types of lean waste. The questionnaire was prepared based on a five point Likert scale for evaluation. It was circulated to the employees of automobile component manufacturing industries participating in international exhibition IMTEX 2015 conducted in Bangalore, India. During this event, 540 industrial exhibitors displayed over 600 machines in three halls. Around 300 overseas companies and 240 Indian companies participated in this machines and tools exhibition. Data was collected from 30 respondents belonging to different countries in the area of automobile component manufacturers. The feedback received from the participants was used for

Table 2. Pairwise comparison matrix for waste types.

Waste	OPN	TPN	WTG	MON	DES	INY	OPG
OPN	1	1	1/5	1/4	1	1/4	1
TPN	1	1	1/2	1/2	1/2	1/2	1/2
WTG	5	2	1	1	1	2	2
MON	4	2	1	1	1/2	3	1/2
DES	1	2	1	2	1	2	1
INY	4	2	1/2	1/2	1/2	1	1
OPG	1	2	1/2	2	1	1	1

Table 3. Consistency check for AHP results.

Type of waste	AHP	Percentage
Overproduction	0.086	8.6%
Transportation	0.080	8.0%
Waiting	0.209	20.9%
Motion	0.165	16.5%
Defects	0.190	19.0%
Inventory	0.115	11.5%
Overprocessing	0.156	15.6%

Consistency check results obtained is 10%.

ranking lean waste. The authors state that the results obtained are related only to the data obtained from the automobile industry in India and abroad. Hence, there is no generalization. Respondents were from various automobile component manufacturing industries holding various positions such as senior managers, engineers, production managers and lean experts. The fuzzy AHP validation could be done easily using the small number of samples to produce crisp results. With this in mind, a minimum of 30 questionnaire samples were collected from the respondents for the analysis. Ramanathan [26] has compared the eight alternatives on the basis of a single criterion and 28 judgements in all and used them for evaluation. Apart from the justifiability herein there is the fact that the 30 companies chosen are those implementing lean production which is the topic of this paper.

The feedback received from the respondents was entered in an excel sheet based on the values obtained in five point Likert scale. The mean and mode values were calculated. Forman and Peniwati [27] stated that when respondent's acts as individuals, one may consider either geometric mean or arithmatic mean of their resulting priorities. The arithmatic mode value was used for the pairwise comparison from the collected survey values. The arithmatic mode values obtained for over production and transportation were taken as 1, for overproduction and waiting as 1/5, for transportation and motion as 1/2, for overproduction and defects as 1, for overproduction and inventory as 1/4, for overproduction and over processing as 1. Similarly, the arithmatic mode values tabulated and shown in Table 2, were computed by comparing the first mentioned waste with every other out of the six relevant wastes. The results indicate consistency of data obtained for further validation.

The consistency index was 0.137457 and the randomized index 1.34. The consistency ratio was calculated using the formula CI/RI = 0.1374/1.34 = 0.102234. Such calculated consistency ratio 10% results are shown in Table 3. After checking the consistency of the data, the next step is to rank the lean waste using fuzzy AHP. The detailed procedure of fuzzy AHP is explained in Section 5.2.

5.2. Prioritize the Lean Waste Using Fuzzy AHP

Step 1. Identify the l, m and u values for each pair of waste.
The aggregated fuzzy comparison matrix is charted using the mode values obtained from Table 2. In Fuzzy AHP, the Triangular Fuzzy Number (TFN) can be represented by l, m and u values for every mode value. These fuzzy numbers are used to quantify a subjective measurement in a range rather than exact value. The l, m, u values were obtained from the linguistic scale of TFN. The linguistic scale of TFN used in this study is based on the work done by Liou and Wang [28] as stated in Table 4.

Table 4. Linguistics scale of TFNs
(Source: Liou and Wang [26]; range is between 0 and 1).

Meaning of linguistic scale	Numerical scale
Very Low (VL)	0, 0, 0.3
Low (L)	0, 0.3, 0.5
Medium (M)	0.2, 0.5, 0.8
High (H)	0.5, 0.7, 1
Very High (VH)	0.7, 1, 1

The l, m and u values obtained from the TFN table were entered in the excel sheet for calculating the column total for each set of values.

Step 2. Find the row and column total for lower, middle and upper values using the excel sheet.

Step 3. Find the grand total of l, m and u values.
The sum of all the l, m and u values are calculated and represented as L, M and U and its grand total S are tabulated as shown in Table 5.

Table 5. Grand total of all l, m and u.

Type of waste	Total of all the l, m and u values		
	L	M	U
Overproduction	6.42857	4.8571	14
Transportation	1	17.666	11.3
Waiting	1.7	2.9	4.1
Motion	1.7	9.1666	10.633
Defects	1	1.9	9.4666
Inventory	6.5	10.666	11.083
Overprocessing	1	4.9333	4.9
Total (S)	19.3285	52.090	65.483

Step 4. Find the inverse of the grand total (S^{-1}).
The L, M and U values obtained are represented as S and the inverse of S was calculated using the formula $S(1/u, 1/m, 1/l)$ where as stated in Table 6. The S_i (where $i = 1, \ldots, 7$) values were calculated by multiplying the S values for all seven types of waste with the inverse of S.

Step 5. Find the degree of possibility of superiority using the conditions stated below.
The degree of possibility of superiority for all seven wastes is calculated by comparing the values $V(S_1 \geq S_2) = 0.742$, $V(S_1 \geq S_3) = 0.439$, $V(S_1 \geq S_4) = 0.894$, $V(S_1 \geq S_5) = 1$, $V(S_1 \geq S_6) = 0.848$ and $V(S_1 \geq S_7) = 0.997$, respectively. In a similar manner compare all S values for the seven types of waste with respect

Table 6. Find the grand total of l, m and u values.

Type of waste	Total of all the l, m and u values		
	L	M	U
S	19.32857	52.09048	65.48333
	$1/u$	$1/m$	$1/l$
Inverse of S	0.015271	0.019197	0.051737

Table 7. Degree of possibility of superiority.

S^{-1}	L	M	U
S_1	0.0982 (l)	0.0932 (m)	0.7243 (u)
S_2	0.0153	0.3392	0.5846
S_3	0.026	0.9835	2.397
S_4	0.026	0.176	0.5501
S_5	0.0153	0.0365	0.4898
S_6	0.0993	0.2048	0.5734
S_7	0.0153	0.0947	0.2535

to the conditions stated below and the S_1 to S_7 values as stated in Table 7.

$$V_1(S_1 \geq S_2)\begin{cases} 1 & \text{If } m_1 > m_2 \\ 0 & \text{If } l_2 > u_1 \\ & \text{Otherwise} \\ & \frac{l_2 - u_1}{(m_1 - u_1) - (m_2 - l_2)} \end{cases}$$

Step 6. Find the normalized value using $\sum w_i$.

$$\sum w_i = \text{Total } (T) \; = \; \text{min of } v(s_1) + \text{min of} v(s_2) + \text{min of } v(s_3)$$
$$+ \text{min of } v(s_4) + \text{min of } v(s_5) + \text{min of} v(s_6) + \text{min of } v(s_7)$$
$$\text{Total } (T) = 0.4395 + 0.4643 + 1 + 0.3936 + 0.3287 + 0.4117 + 0.2038$$
$$T = 3.24291985$$

Step 7. Find the normalized weighted vector for the lean waste.
The normalized weighted vector values for all the seven wastes are calculated separately by dividing the minimum of the degree of possibility of superiority with the Total (T). The various values obtained are as follows min $v(s_1)/T = 0.1355$, min $v(s_2)/T = 0.1431$, min $v(s_3)/T = 0.3083$, min $v(s_4)/T = 0.1213$, min $v(s_5)/T = 0.1013$, min $v(s_6)/T = 0.1272$, min $v(s_7)/T = 0.0628$.

Step 8. Rank the lean waste.
The seven types of waste are ranked on the basis of the values obtained from the Fuzzy AHP results. The waiting waste is ranked 1 with the Fuzzy AHP value of 0.3083. The other six lean waste items are ranked on the basis of Fuzzy AHP values obtained, viz., Transportation (0.1431) – Rank 2; Overproduction (0.1355) – Rank 3; Inventory (0.1273) – Rank 4; Motion (0.1214) – Rank 5; Defects (0.1013) – Rank 6; and Overprocessing (0.0629) – Rank 7, respectively.

The graphical representation and the practical problem solving, show the contribution of waiting as much more than for any other waste in automobile component manufacturing industries. The fuzzy AHP values obtained for the other type of waste are as indicated in Fig. 2. The various contributing factors are taken into consideration for further statistical analysis for detailed investigation.

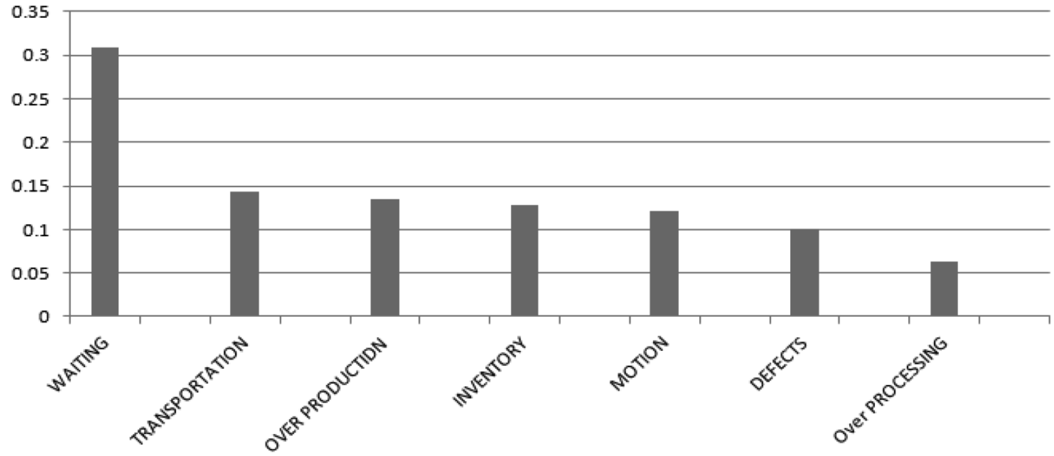

Fig. 2. Ranking of the seven lean waste.

6. ANALYSIS OF CONTRIBUTING FACTORS

6.1. Factors for Waiting

Since waiting is the major waste, the most dominating sub factors that cause the waiting waste in the automobile component manufacturing industries are identified. Eleven major contributing factors are known to cause the waiting waste through various literatures. The major subfactors are listed below:

1. Unbalanced process
2. Non-availability of materials
3. Operator waiting
4. Distance between work centers
5. Poor communication
6. Waiting for next operations
7. Breakdown
8. Unload and load cycle time
9. Rework and waiting
10. Waiting at quality checking area
11. Deburring and inspection

Among these 11 factors, the major three contributing factors are identified using BLR for the waiting waste.

6.2. Binary Logistic Regression (BLR) Model

BLR is a method of choice when the dependent variable is binary. In this work, the mean value of the waiting waste is calculated from the collected data and the sample size is 104 in number. The BLR model is assessed using the statistical test of individual predictors, goodness of fit statistics, validations of predicted possibilities and the overall model evaluation as stated in [29]. From the responses collected, the calculated

Table 8. Response summary – waiting.

Value	Count	Proportion	Reference Event
0	36	0.346153846	
1	68	0.653846154	X
Total	104		

Table 9. Parameter estimates.

Term	P value
Unbalanced Process	0.6096
Non-availability of materials	0.5083
Operator waiting time	**0.0248**
Distance between work centers	**0.0046**
Poor communication	0.3501
Waiting for next operation	0.0938
Breakdown	0.7349
Unload and load cycle time	**0.0184**
Rework and waiting	0.1803
Waiting at quality checking area	0.8445
Deburring and inspection	0.0525

mean obtained is 2.6267 which is approximately equal to 3. The binary value assigned for obtaining value greater than or equal to 3 is 1. It is zero when the binary value is less than 3. Using the BLR model, the regression equation framed for the 11 contributing subfactors of the waiting waste is

$$\begin{aligned}\mathrm{Ln}(Py/(1-Py)) = {} & (-4.680)+(-0.157485)*\text{Unbalanced process}\\ & +(-0.176554)*\text{Non-availability of materials}\\ & +(0.570851)*\text{Operator waiting}+(0.824487)*\text{Distance between work centers}\\ & +(0.251070)*\text{Poor communication}+(0.019464065)*\text{Waiting for next operations}\\ & +(0.056953548)*\text{Breakdown}+(0.639934)*\text{Unload and load cycle time}\\ & +(-0.386361)*\text{Rework and waiting}\\ & +(-0.051895853)*\text{Waiting at quality checking area}\\ & +(0.457502)*\text{Deburring and inspection.}\end{aligned}$$

Out of 104 respondents, the results of 36 were below the mean and those of 68 were above the mean. The reference event was taken as X as shown in Table 8. Referring to Table 9, the values indicated in bold show the significance of those three factors. The three factors and their P values are: Operator waiting time (0.248), Distance between work centers (0.0046), Unloading and loading cycle time (0.0184). The contribution of these three factors to the waiting waste is higher when the significance level is 5%.

6.3. McFadden's R-Squared Tests

In McFadden's Pseudo R-Squared test, the result should be in the range of 10 to 40%. The result obtained from the McFadden's Pseudo R-Square is 14.23%. It indicates that these three factors satisfy the McFadden's R-Squared test as shown in Table 10.

Table 10. McFadden's R-Squared test.

Test that all slope coefficients are equal to zero:	
Likelihood Ratio Chi-Square (G)	19.096
DF	11
P Value	0.0594
McFadden's Pseudo R-Square	14.23%
Log-Likelihood	–57.535

Table 11. Pearson, Deviance and Hosmer–Lemeshow goodness of fit.

Goodness-of-Fit Tests (P Value $<$ .05 indicates Lack-of-Fit):	
Pearson Residuals Chi-Square	60.112
DF	44
P Value	0.0534
Deviance Residuals Chi-Square	65.789
DF	44
P Value	0.0583
Hosmer–Lemeshow Chi-Square	13.697
DF	7
P Value	0.0568

6.4. Pearson, Deviance and Hosmer–Lemeshow Goodness of Fit

The P value obtained for Pearson Residuals Chi-Square is 0.0534, Deviance Residuals Chi-Square is 0.0583 and Hosmer–Lemeshow Chi-Square is 0.0568. All the p-values being greater than 0.05 indicates the significance of these three factors through the satisfaction of the various tests shown in Table 11.

6.5. Response Event Probability

The probability value of the predicted event is 0.9959. It is obtained from the Response event probability table. This value indicates the operating waiting time, distance between the work centers and load and unload cycle time as the major factors out of 11 factors as shown in Table 12.

Table 12. Response event probability.

Predictors	Enter Settings	Predicted Event Probability
Unbalanced process	0	0.9959170
Non-availability of materials	0	
Operator waiting time	5	
Distance between work centers	5	
Poor communication	0	
Waiting for next operations	0	
Breakdown	0	
Unload and load cycle time	5	
Rework and waiting	0	
Waiting at quality checking area	0	
Deburring and inspection	0	

Table 13. Observed and predicted outcomes.

Observed Outcome	Predicted Outcome		
	$\hat{Y}=0$	$\hat{Y}=1$	Row Total
$Y=0$	12	24	36
$Y=1$	10	58	68
Column Total	22	82	104
Percent Correctly Predicted	65.38%		

6.6. Observed and Predicted Outcomes

In Table 13, the row total value for $Y=0$ is 36 while it is 68 for $Y=1$. The predicted percentage has been calculated using the formula: No of favourable respondents/Total number of respondent's, i.e. $68/104 = 65.38\%$. The total number of respondents is 104. The predictions proved right with 65.38% thereof. Hence these three factors are taken as the major contributing factors satisfying the various chi-square tests as shown in Table 11.

7. CONCLUSION

Identification and elimination of lean wastes are the main targets in today's industrial scenario. Automobile component manufacturing industries have been selected in order to find the major lean wastes and their dominating factors. Data collection is carried out using the questionnaire. The pairwise comparison matrix for the lean wastes is calculated. The consistency of the data is checked by using the AHP algorithm and found to be 10%. Since the AHP data validation results are positive, Fuzzy AHP algorithm is used to detect the major lean waste out of seven types of waste. From the seven lean wastes, waiting is found to be the major lean waste using Fuzzy AHP with the value of 20.9%. Eleven contributing factors for the waiting waste are listed on the basis of the literature review. The major three factors out of 11 factors are identified using BLR. These are operator waiting time, distance between work centers, unload and load cycle time. The P values for the three dominating factors are 0.0218, 0.0046 and 0.0184, respectively. Moreover the McFadden pseudo square test value is 14.23%, which is within the acceptable range. The Pearson, Deviance and Hosmer–Lemeshow test P values are greater than 0.05 and the calculated P values are 0.0534, 0.0583 and 0.0568, respectively. The response event probability also indicates these three as major factors standing out of 11 factors. The results obtained are predicted correctly with the value of 65.38%. The result indicates the requirement for reduction of these three factors for the productivity improvement. When the waiting time of operators is considerably reduced, there will be a drastic increase in the production rate. When there is a reduction in the distance between the work centers, movements of the men, machine and materials are optimized. Reduction in the loading and unloading time results in increase of machine hour availability. Future research may focus on the Fuzzy AHP and BLR for use in prioritization of the other types of lean waste for productivity improvement using lean systems.

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