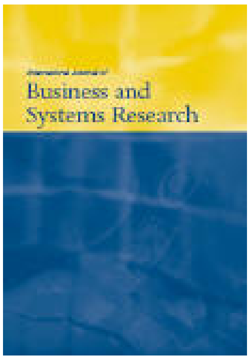


International Journal of Business and Systems Research

ISSN online: 1751-2018 - ISSN print: 1751-200X
https://www.inderscience.com/ijbsr

Productivity improvement in a paper manufacturing company through lean and IoT - a case study

K.R. Shriram, S. Kishore Karthiban, A. Charan Kumar, S.K. Mathiarasu, P.G. Saleeshya

DOI: 10.1504/IJBSR.2022.10036457

Article History:

Received:	13 August 2020
Accepted:	20 November 2020
Published online:	15 December 2022

Productivity improvement in a paper manufacturing company through lean and IoT – a case study

K.R. Shriram, S. Kishore Karthiban,
A. Charan Kumar, S.K. Mathiarasu and
P.G. Saleeshya*

Department of Mechanical Engineering,
Amrita School of Engineering,
Amrita Vishwa Vidyapeetham,
Coimbatore, India
Email: shriramrajsekar@gmail.com
Email: kishores98@outlook.com
Email: chara4499@gmail.com
Email: mathikesavan20@gmail.com
Email: pg_saleeshya@cb.amrita.edu
*Corresponding author

Abstract: Industries implemented lean techniques experienced a saturation of leanness after a certain period of time. This forced them to look out for optimised lean models. The combination of lean and the internet of things (IoT) promise astonishing advances in the improvement of leanness. This paper focuses on the improvement of leanness with the aid of IoT systems. A case study was performed in a leading board paper manufacturing industry. Fuzzy logic-based lean assessment model assessed the leanness of the industry. Lean tools like value stream mapping, root cause analysis, Jidoka, etc. were performed to identify and eliminate the lean wastes. IoT-based systems were modelled. Leanness of the industry was computed before implementation, after lean implementation and after IoT implementation. The results were used to contrast the improvements shown by lean practices and IoT systems individually, and proved that the combination of lean and IoT have a greater potential for industries in the future.

Keywords: lean manufacturing; leanness; lean index; fuzzy logic; digitalisation; internet of things; IoT.

Reference to this paper should be made as follows: Shriram, K.R., Karthiban, S.K., Kumar, A.C., Mathiarasu, S.K. and Saleeshya, P.G. (2023) 'Productivity improvement in a paper manufacturing company through lean and IoT – a case study', *Int. J. Business and Systems Research*, Vol. 17, No. 1, pp.97–119.

Biographical notes: K.R. Shriram graduated from Amrita School of Engineering Coimbatore with Mechanical Engineering as the main stream. He is currently working as an Assistant System Engineer-Trainee in Tata Consultancy Services (TCS), Chennai. His fields of interest are lean manufacturing, Six Sigma and supply chain management.

S. Kishore Karthiban is an undergraduate Mechanical Engineer from Amrita School of Engineering, Coimbatore. He is currently working as an Assistant System Engineer-Trainee in Tata Consultancy Services (TCS), Bangalore. His fields of interest include lean manufacturing, supply chain management, logistics and heat treatment.

A. Charan Kumar successfully graduated Mechanical Engineering from Amrita Vishwa Vidyapeetham, Coimbatore. He is currently working as an Area Manager-Operations in Amazon, Chennai. His areas of expertise are lean manufacturing, operations project management and supply chain management.

S.K. Mathiarasu is an undergraduate Mechanical Engineer from Amrita Vishwa Vidyapeetham University, Coimbatore. He is currently working as Systems Engineer-Trainee in Infosys. His areas of interest are lean manufacturing and supply chain management.

P.G. Saleeshya is a Professor of Mechanical Engineering at the Amrita University, Coimbatore, India. She received her PhD in Industrial Engineering and Operations Research (Agile Manufacturing) from Indian Institute of Technology, Bombay, India. Her areas of interest in teaching and research is mainly focused on operations strategy: agile manufacturing, lean manufacturing, Lean Six Sigma, green design and manufacturing, and responsive supply chain, agility in textile industries. She has several publications in various international journals.

1 Introduction

Lean manufacturing is the process of minimising non-value added activities present in industries for improved overall performance. The non-value added activities accounts to nine wastes of lean. By eliminating these wastes from the production line, overall performance can be improved. Over the past two decades, many industries have adopted lean as a culture to improve productivity and to sustain the increasing competition. There has been rapid growth in the technology sector over the past decade. These technologies have been constantly replaced or incorporated with conventional techniques for improved effectiveness. Many industries which have been adopting lean for considerably a longer period encountered a problem; the improvement in productivity becomes saturated. To counteract this problem, digitalisation approach is adapted (Prinza et al., 2018). Digitalisation techniques incorporated with conventional lean techniques can be implemented to enhance productivity.

1.1 Uniqueness of the research work

Though researchers have been contributing certain theoretical explanations for the need of digitalisation, there existed a need for an industrial-case scenario to prove it evidentially. A leading paper manufacturing company has been chosen for study. A fuzzy-logic-based lean assessment tool has been used to assess the leanness of the company. Various lean tools like value stream mapping (VSM), fish bone diagram has been used to identify and eliminate the wastes in the company. Lean methodologies and digitalisation models have been implemented. Internet of things (IoT) is used as a tool for digitalisation. IoT is a system of devices capable of internet connectivity for identifying, sensing, networking, and computation which enables large-scale technological innovations and personalised user services. In simple words, IoT is a process where machines communicate with each other without human interference. Also, lean index has been computed at various scenarios to contrast the improvements shown by digitalisation. Lean index is computed to quantify the leanness of production system. The uniqueness of the study is that it is an attempt to evidentially prove the need for digitalisation to overcome the drawbacks associated with the traditional lean methodologies.

The paper is structured as follows. Section 2 reviews on lean systems, lean assessment models and fuzzy logic, Section 3 reviews on the methodology of the research work. Section 4 presents the detailed study of the system, Section 5 presents the development of lean assessment model, Section 6 presents the lean assessment of the existing system, Section 7 elaborates on the identified problems and the application of lean methodologies in the existing system, Section 8 presents the lean assessment of the system post-lean implementation, Section 9 presents the development of IoT models, Section 10 presents the lean assessment of the system post-IoT implementation. Analysis of the results, conclusion and future scope of work are discussed in Section 11.

2 Literature review

The term ‘lean manufacturing’ was first coined by John Krafcik in 1982. Lean manufacturing focuses on the elimination of waste (Muda), overburden (Muri), and variation (Mura). Muda, Muri, and Mura are called the three M’s, also known as the enemies of lean (Liker, 2004). However, it is not entirely possible to eliminate them. Therefore, reducing all three M’s is the priority of organisations. Shah and Ward (2003) contrasted the effects of three contextual factors to implement 22 manufacturing practices that are essential to lean production systems (LPS). Further, they selected inter-related practices to merge into four practice bundles associated with just-in-time (JIT), total predictive maintenance (TPM), total quality management (TQM) and human resource management (HRM). Saleeshya et al. (2015) developed an optimal scheduling sequence algorithm in the context of lean manufacturing. They showcased how VSM can be utilised to map the current status of the production and illustrated how VSM could provide the necessary information to identify the scope of improvement. In this study, they validated the results with lean tools such as 5S, cause-and-effect diagram, Pareto analysis, five-why analysis and VSM.

The formulation of lean assessment models was initiated in 1996 by Karlsson and Ahlstrom. Bayou and de Korvin (2008) developed a fuzzy-logic-based leanness measure. By considering Honda Motor Company as the benchmarking firm, they found that the Ford motor production system is 17% leaner than the General Motors production system. Vinodh and Chintha (2009) developed a fuzzy-logic-based leanness assessment model.

Also, by substitution of data gathered from an organisation, leanness index and areas for improvement was identified. In another study, Vinodh and Vimal (2012) designed a 30-criterion-based leanness assessment model using fuzzy logic. To counteract the obscurity associated with the fuzzy-based leanness measure, Delgado et al. (1992) suggests the usage of triangular and trapezoidal membership functions over any other membership functions. Saleeshya and Binu (2019) developed a neuro-fuzzy hybrid model for measuring the leanness of the manufacturing systems. Using analytical hierarchy process (AHP), Saleeshya et al. (2013) developed a model capable of identifying lean tools and enablers that show high impact on LPS.

Kevin Ashton coined the term 'IoT' in 1999. IoT is a system of real-time objects embedded with software that is capable of exchanging information between them. Addition of sensors to all the interconnected physical devices allows them to communicate real-time data without the involvement of a human being. The industrial application of IoT is known as the industrial internet of things (IIoT). Boyes et al. (2018) reviews the definition of IIoT and relationships to the concepts of Industry 4.0. Hoellthaler et al. (2019) explain the potential of digitalisation to initiate a third wave within the philosophy of lean production. Further, explains the methodology for the assessment and selection of technologies for LPS. Prinza et al. (2018) explain the slowdown in productivity improvement after lean implementation. Also, explains the role of digitalisation in productivity improvement.

2.1 Overview of lean tools and concepts

The common lean tools and concepts are elaborated below:

- 5S: Focuses on eliminating waste that results from poorly organised work environment. 5S is achieved by focusing on improved workplace organisation and standardised work policies.
- Poka-yoke: An approach that focuses on eliminating product defects by preventing, correcting or drawing attention to human errors.
- TPM: A maintenance approach focusing on proactive and preventive maintenance to increase the overall operating time of machinery.
- VSM: A visualisation tool used to map the process flow of the production system. It helps in identifying the waste in the current system and paves a path for improvement in the future.
- Jidoka: Also, known as autonomation. An approach to protect the system from delivering low quality and defective products. It mainly relies on five basic principles – discovers an abnormality, stops the process, fixes the problem immediately, investigate the root cause and solve the root cause.
- Root cause analysis: Also, known as the fish-bone diagram. A methodology that focuses on identifying and highlighting the possible causes of a specific problem. Also, diagrammatically displays the relationship between a specific problem and the factors contributing to that specific problem.

- Kaizen: A strategy where all employees from line workers to CEO work together to achieve continuous improvement in the manufacturing process.
- JIT: A strategy that delivers inventory and products when, and only when they are necessary. Also, it will reduce excess inventory. Adoption of JIT will eventually lead to short production runs, less dead stock, smaller warehouses and better cash flow.
- Kanban: A visual signalling system to manage work as it moves a series of processes in a manufacturing system. It aims to identify and fix the bottlenecks in the process efficiently.

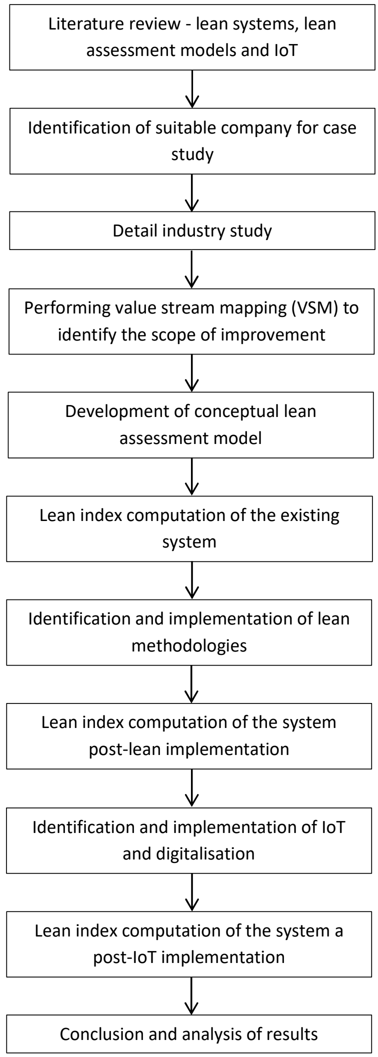
3 Methodology

Figure 1 depicts the sequential steps followed during the study. The detailed literature review revealed the need for optimised lean models. The case company adhering to the objective has been identified. A detailed study has been performed to understand the process flow of the system. VSM has been performed to identify the scope of improvement. A conceptual model has been developed to assess the leanness of the company, which is divided into two tiers namely enablers and attributes. A team comprising of three experts has been formed. The experts are the chiefs of crucial departments in the company. Experts evaluated the performance rating of lean attributes and the importance weights of lean attributes using linguistic variables. The linguistic variables are then converted to their corresponding triangular fuzzy numbers. Lean index of the company has been computed using fuzzy logic. The weakly performing lean attributes have been identified. Root cause analysis has been performed to address the presence of non-value added activities in the system. Lean methodologies have been proposed to eliminate the non-value added activities. Again, the lean index has been computed after lean implementation. The scope of introducing IoT and digitalisation has been identified. IoT systems have been modelled and proposed. Again, the lean index has been computed after IoT implementation. The computed lean index values before lean implementation, after lean implementation and after IoT implementation has been contrasted to draw the conclusion and discuss the future scope of work.

4 Case study

The case study has been conducted in a leading paper manufacturing company located in South India. The company has been struggling to achieve production as per demand. Also, frequent breakdowns and increased defects affected the productivity of the company. There existed a need for the company to reduce breakdowns and defects for improved productivity. So, our paper focuses on productivity improvement with the help of lean and IoT initiatives.

Figure 1 Research methodology



4.1 Analysis of the existing system

The first step would be to identify the scope of improvement in the system through VSM. VSM is a lean tool that helps to visualise the sequential processes needed from procurement of raw materials to end-customer delivery (Rother and Shook, 1999). Also, it helps to analyse the process flow, identify waste and inefficiencies present in the system. The VSM of the existing system is shown in Figure 2.

The VSM has been performed for the production demand of 300 tonnes. Figure 2 shows the lead time taken to produce 300 tonnes of paper is 4.59 days. The value added time accounts to 3.75 days and the non-value added time accounts to 0.84 days. The non-value added activities add up to 19% of the total activity duration, revealing the scope of improvement in the system. Table 1 displays the detailed analysis of the VSM.

Figure 2 VSM of the existing system (see online version for colours)

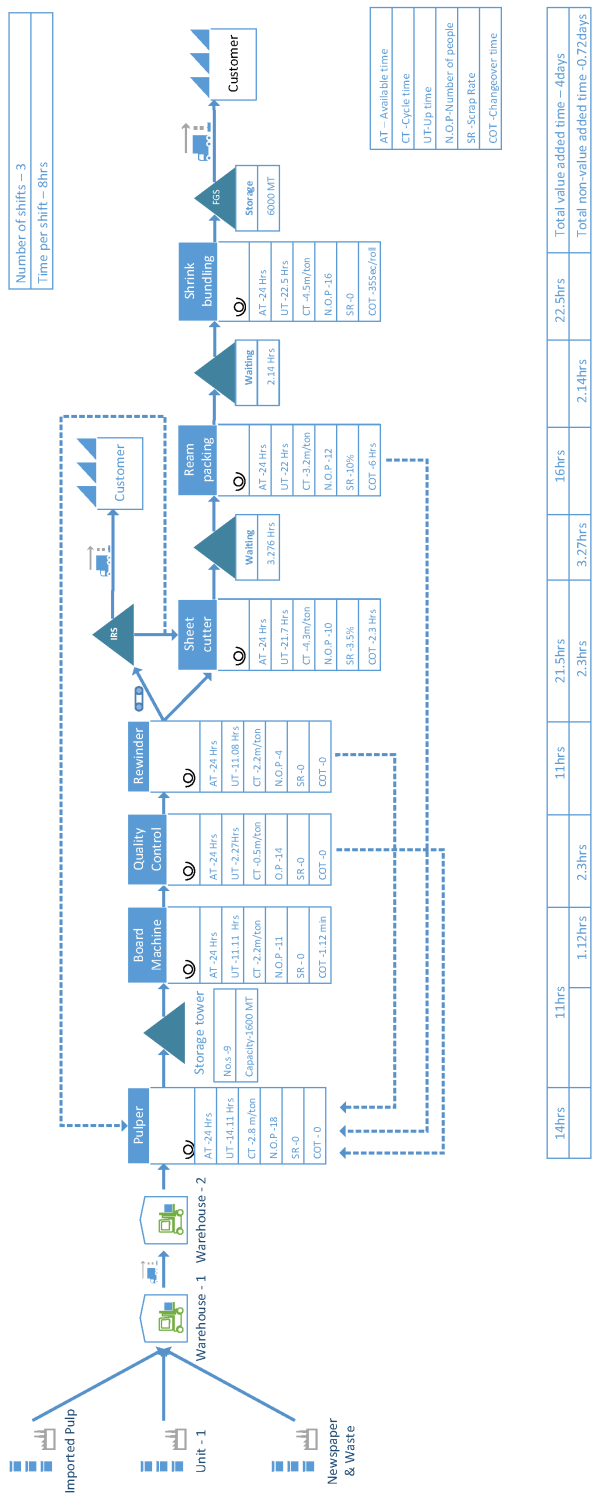


Table 1 Analysis of VSM

	VA time	*NVA time*
Pulper	14 hrs	-
Board-machine	10 hrs	1.12 hrs
Quality control	-	2.38 hrs
Rewinder	11.08 hrs	-
Sheet cutter	19.40 hrs	2.3 hrs
Ream packing	*16.05 hrs*	9.27 hrs
Shrink bundling	19.60 hrs	5.09 hrs
Total	**90.13 hrs**	**20.16 hrs**

Table 2 Conceptual model for leanness assessment

	Lean attributes	
S. no.	*Tier one*	*Tier two*
1	Use of space and movement of materials (LA_1)	Efficient movement of materials (LA_{11})
		Material storage in appropriate containers (LA_{12})
		Organised storage of materials (LA_{13})
2	Inventory management (LA_2)	Appropriate inventory levels at each stage (LA_{21})
		Tracking inventory on hand and in order (LA_{22})
		FIFO inventory management system (LA_{23})
3	Scheduling system (LA_3)	Pull with continuous flow system (LA_{31})
		Scheduling based on varying demand (LA_{32})
		Steps taken to avoid waiting time (LA_{33})
4	Resource management (LA_4)	Effective resource management (LA_{41})
		Real-time monitoring system (LA_{42})
		Steps taken to avoid over processing (LA_{43})
5	Quality control (LA_5)	Timetable posted for effective preventive maintenance and ongoing improvement of tools and processes (LA_{51})
		5S (sort, set-in-order, shine, standardise, and sustain) (LA_{52})
		Quality inspection (LA_{53})
6	Safety environment (LA_6)	Working in safe, clean, orderly and well-lit environment (LA_{61})
		Quality of air and noise level (LA_{62})
		Effluent treatment (LA_{63})
7	Flexibility of production system (LA_7)	On-time delivery of varying products (LA_{71})
		Production of new features according to market demand (LA_{72})
		Ability to modify the production system if needed (LA_{73})
8	Management of variation (LA_8)	Management of process variations (LA_{81})
		Management of variations in individual performances (LA_{82})
		Continuous monitoring on skill sets of an individual (LA_{83})
9	Maintenance (LA_9)	Management of machinery breakdowns (LA_{91})
		Real-time monitoring of machineries (LA_{92})
		Total predictive maintenance (LA_{93})

Table 2 Conceptual model for leanness assessment (continued)

Lean attributes		
S. no.	*Tier one*	*Tier two*
10	Digitalisation-IoT (LA_{10})	Systems involving advanced technologies like IoT and cloud computing (LA_{101})
		Real-time monitoring of the industry (LA_{102})
		System to deliver security alert via SMS/mail (LA_{103})

5 Development of lean assessment model

The conceptual model has been developed and is shown in Table 2. The model is partitioned into two tiers. It corresponds to 10 tier-one attributes, 30 tier-two attributes. All the lean attributes have been chosen based on detailed industry study and expert opinion. For example, usage of space and movement of materials is a tier-one lean attribute. 'Usage of space and movement of materials' comprises of tier-two attributes such as "efficient movement of materials, material storage in appropriate containers and organised storage of materials." All these tier-two attributes are linked to corresponding tier-one attribute based on similarity and functionality. Each of these tier-two attributes contributes to corresponding tier-one attributes in terms of performance.

5.1 Lean assessment using fuzzy logic

The lean index is computed to quantify the inclination of the company towards lean manufacturing practices. Fuzzy logic has been utilised over any other approaches is to counteract the ambiguity and vagueness associated with the leanness assessment. To experience varied opinions from different perspectives, three experts participated in assessing the leanness of the company individually. Experts are the chiefs of various critical departments including quality control, maintenance and production. Experts assessed the performance rating and importance weightage of lean attributes using linguistic variables. For performance rating, seven scale responses are developed to label the degree of implementation of lean attributes in the existing system. Also, for importance weightage, seven scale responses are developed to label the degree of importance of lean attributes in the existing system (Saleeshya and Binu, 2019). These seven scale responses are correlated to triangular fuzzy numbers using linguistic terms. The expert's linguistic responses are transformed into their corresponding fuzzy numbers using Tables 3 and 4. The correlation between the triangular fuzzy numbers and the performance ratings is shown in Table 3. Also, the correlation between the triangular fuzzy numbers and the importance weightages is shown in Table 4.

The lean index of a tier-one lean attribute is computed by dividing the sum product of corresponding performance ratings and importance weightages of tier-two attributes by the total of the importance weightage of tier-two attributes. The tier-one fuzzy lean index, FLIi is computed by using equation (1).

$$FLI_i = \sum_{j=1}^{N} \left(P_{ij} \times W_{ij} \right) \div \sum_{j=1}^{N} W_{ij} \tag{1}$$

FLI_i fuzzy lean index of i^{th} tier-one lean attribute

P_{ij} performance rating for ij^{th} tier-two lean attribute

W_{ij} importance weightage for ij^{th} tier-two lean attribute.

Table 3 Performance rating

Performance rating			
Linguistic variable	*Triangular fuzzy number*		
Unacceptable (*U*)	0	0.5	1.5
Inadequate (*IA*)	1	2	3
Adequate (*A*)	2	3.5	5
Fair (*F*)	3	5	7
Good (*G*)	5	6.5	8
Very good (*VG*)	7	8	9
Excellent (*E*)	8.5	9.5	10

Table 4 Importance weightage

Importance weightage			
Linguistic variable	*Triangular fuzzy number*		
Very low (*VL*)	0.0	0.05	0.15
Low (*L*)	0.1	0.2	0.3
Fairly low (*FL*)	0.2	0.4	0.5
Medium (*M*)	0.3	0.5	0.7
Fairly high (*FH*)	0.5	0.65	0.8
High (*H*)	0.7	0.8	0.9
Very high (*VH*)	0.85	0.95	1

The model lean indices for 'usage of space and movement of materials', the first tier-one attribute is shown in Table 5. The computation of the lean index for 'usage of space and movement of materials', the first tier-one lean attribute is depicted below:

$$FLI_1 = \frac{\left[\{(P_{11})\otimes(W_{11})\}\oplus\{(P_{12})\otimes(W_{12})\}\oplus\{(P_{13})\otimes(W_{13})\}\right]}{\left[(W_{11})\oplus(W_{12})\oplus(W_{13})\right]}$$

Table 5 Model lean indices of 'usage of space and movement of materials'

LA_i	LA_{ij}	W_i	W_{ij}	P_{ij}
LA_1	LA_{11}	W_1	W_{11}	P_{11}
	LA_{12}		W_{12}	P_{12}
	LA_{13}		W_{13}	P_{13}

Likewise, the lean indices are computed for all tier-one lean attributes. Overall lean index of the company is represented by OLI. The overall lean index of the company is computed by dividing the sum product of corresponding performance ratings and importance weightages of tier-one attributes by the total of the importance weightage of tier-one attributes. Equation (2) for the overall lean index is

$$OFLI = \sum_{i=1}^{10} (P_i \times W_i) \div \sum_{i=1}^{10} W_i \quad 2)$$

OFLI overall fuzzy leanness index of the company

P_i performance rating of i^{th} tier-one lean attribute

W_i importance weightage of i^{th} tier-one lean attribute.

The model lean indices of tier-one lean attributes are shown in Table 6. The computation of the overall lean index of the company is depicted below:

$$OFLI = \frac{\begin{bmatrix} \{(P_1)\otimes(W_1)\}\oplus\{(P_2)\otimes(W_2)\}\oplus\{(P_3)\otimes(W_3)\} \\ \oplus\{(P_4)\otimes(W_4)\}\oplus\{(P_5)\otimes(W_5)\}\oplus\{(P_6)\otimes(W_6)\} \\ \oplus\{(P_7)\otimes(W_7)\}\oplus\{(P_8)\otimes(W_8)\}\oplus\{(P_9)\otimes(W_9)\} \\ \oplus\{(P_{10})\otimes(W_{10})\} \end{bmatrix}}{\begin{bmatrix} (W_1)\oplus(W_2)\oplus(W_3)\oplus(W_4)\oplus(W_5) \\ \oplus(W_6)\oplus(W_7)\oplus(W_8)\oplus(W_9)\oplus(W_{10}) \end{bmatrix}}$$

Table 6 Model lean indices of tier-one lean attributes

No.	*Tier-one attributes*	LA_i	*Importance weightage (W_i)*	*Performance rating (P_i)*
1	Use of space and movement of materials	LA_1	W_1	P_1
2	Inventory management	LA_2	W_2	P_2
3	Scheduling system	LA_3	W_3	P_3
4	Resource management	LA_4	W_4	P_4
5	Quality control	LA_5	W_5	P_5
6	Safety environment	LA_6	W_6	P_6
7	Flexibility of production system	LA_7	W_7	P_7
8	Management of variation	LA_8	W_8	P_8
9	Maintenance	LA_9	W_9	P_9
10	IoT-digitalisation	LA_{10}	W_{10}	P_{10}

The performances of lean attributes are assessed with the aid of weighted performance. Product of the performance rating and the importance weightage results in the weighted performance of the lean attribute. Equation of weighted performance is

$$WP_i = P_i \times W_i \quad (3)$$

WP_i weighted performance

P_i performance rating of i^{th} tier-one lean attribute

W_i importance weightage of i^{th} tier-one lean attribute.

Weighted performance is a triangular fuzzy number of the form (x, y, z). It has to be converted into a standard real number form to identify the weakly performing lean attributes. The conversion is performed using the following equation.

$$PI = \frac{X + Y + Z}{3} \tag{4}$$

PI performance index

X lower number of triangular fuzzy number

Y intermediate number of triangular fuzzy number

Z upper number of triangular fuzzy number.

6 Lean assessment of the existing system

Lean index of the existing system has been computed to identify the weakly performing lean attributes and to contrast the improvements post-lean implementation. Three experts participated in assessing the leanness of the company. Expert's responses have been recorded in the form of linguistic variables. The first expert's linguistic response is as shown in Table 7. Linguistic responses have been transformed into corresponding triangular fuzzy values using Tables 3 and 4. The first expert's input data is as shown in Table 8.

Table 7 Response sheet

LA_i	LA_{ij}	W_i	W_{ij}	P_{ij}
LA_1	LA_{11}	*VH*	*H*	*A*
	LA_{12}		*H*	*G*
	LA_{13}		*FH*	*IA*
LA_2	LA_{21}	*H*	*L*	*G*
	LA_{22}		*FH*	*G*
	LA_{23}		*VH*	*VG*
LA_3	LA_{31}	*FH*	*H*	*G*
	LA_{32}		*FH*	*F*
	LA_{33}		*H*	*VG*
LA_4	LA_{41}	*FH*	*VH*	*G*
	LA_{42}		*VH*	*A*
	LA_{43}		*H*	*U*
LA_5	LA_{51}	*VH*	*VL*	*A*
	LA_{52}		*VH*	*F*
	LA_{53}		*M*	*A*
LA_6	LA_{61}	*H*	*VH*	*VG*
	LA_{62}		*M*	*F*
	LA_{63}		*H*	*A*

Table 7 Response sheet (continued)

LA_i	LA_{ij}	W_i	W_{ij}	P_{ij}
LA_7	LA_{71}	*FH*	*H*	*VG*
	LA_{72}		*FH*	*G*
	LA_{73}		*FL*	*U*
LA_8	LA_{81}	*H*	*FL*	*A*
	LA_{82}		*L*	*A*
	LA_{83}		*FH*	*G*
LA_9	LA_{91}	*VH*	*H*	*A*
	LA_{92}		*H*	*IA*
	LA_{93}		*H*	*G*
LA_{10}	LA_{101}	*H*	*VH*	*IA*
	LA_{102}		*H*	*A*
	LA_{103}		*H*	*IA*

Table 8 Input data

LA_i	LA_{ij}	W_i	W_{ij}	P_{ij}
LA_1	LA_{11}	(0.85, 0.95, 1)	(0.7, 0.8, 0.9)	(2, 3.5, 5)
	LA_{12}		(0.7, 0.8, 0.9)	(5, 6.5, 8)
	LA_{13}		(0.5, 0.65, 0.8)	(1, 2, 3)
LA_2	LA_{21}	(0.7, 0.8, 0.9)	(0.1, 0.2, 0.3)	(5, 6.5, 8)
	LA_{22}		(0.5, 0.65, 0.8)	(5, 6.5, 8)
	LA_{23}		(0.85, 0.95, 1)	(7, 8, 9)
LA_3	LA_{31}	(0.5, 0.65, 0.8)	(0.7, 0.8, 0.9)	(5, 6.5, 8)
	LA_{32}		(0.5, 0.65, 0.8)	(3, 5, 7)
	LA_{33}		(0.7, 0.8, 0.9)	(7, 8, 9)
LA_4	LA_{41}	(0.5, 0.65, 0.8)	(0.85, 0.95, 1)	(5, 6.5, 8)
	LA_{42}		(0.85, 0.95, 1)	(2, 3.5, 5)
	LA_{43}		(0.7, 0.8, 0.9)	(0, 0.05, 1.5)
LA_5	LA_{51}	(0.85, 0.95, 1)	(0.1, 0.2, 0.3)	(2, 3.5, 5)
	LA_{52}		(0.85, 0.95, 1)	(3, 5, 7)
	LA_{53}		(0.5, 0.65, 0.8)	(2, 3.5, 5)
LA_6	LA_{61}	(0.7, 0.8, 0.9)	(0.85, 0.95, 1)	(7, 8, 9)
	LA_{62}		(0.3, 0.5, 0.7)	(3, 5, 7)
	LA_{63}		(0.7, 0.8, 0.9)	(2, 3.5, 5)
LA_7	LA_{71}	(0.5, 0.65, 0.8)	(0.7, 0.8, 09)	(7, 8, 9)
	LA_{72}		(0.5, 0.65, 0.8)	(5, 6.5, 8)
	LA_{73}		(0.2, 0.4, 0.5)	(0, 0.05, 0.15)
LA_8	LA_{81}	(0.7, 0.8, 0.9)	(0.2, 0.4, 0.5)	(2, 3.5, 5)
	LA_{82}		(0.1, 0.2, 0.3)	(2, 3.5, 5)
	LA_{83}		(0.85, 0.95, 1)	(5, 6.5, 8)

Table 8 Input data (continued

LA_i	LA_{ij}	W_i	W_{ij}	P_{ij}
LA_9	LA_{91}	(0.85, 0.95, 1)	(0.7, 0.8, 0.9)	(2, 3.5, 5)
	LA_{92}		(0.7, 0.8, 0.9)	(1, 2, 3)
	LA_{93}		(0.7, 0.8, 0.9)	(5, 6.5, 8)
LA_{10}	LA_{101}	(0.7, 0.8, 0.9)	(0.85, 0.95, 1)	(1, 2, 3)
	LA_{102}		(0.7, 0.8, 0.9)	(2, 3.5, 5)
	LA_{103}		(0.7, 0.8, 0.9)	(1, 2, 3)

Table 9 Fuzzy lean indices of tier-one lean attributes

LA_i	LA_{ij}	FLI_i	WP_i	PI_i
LA_1	LA_{11}	(2.73, 4.03, 5.34)	(2.32, 3.83, 5.34)	3.83
	LA_{12}			
	LA_{13}			
LA_2	LA_{21}	(6.17, 7.29, 8.47)	(4.32, 5.83, 7.62)	5.91
	LA_{22}			
	LA_{23}			
LA_3	LA_{31}	(5.21, 6.60, 8.03)	(2.60, 4.29, 6.43)	4.42
	LA_{32}			
	LA_{33}			
LA_4	LA_{41}	(2.47, 3.67, 4.94)	(1.23, 2.38, 3.95)	2.52
	LA_{42}			
	LA_{43}			
LA_5	LA_{51}	(2.58, 4.29, 5.95)	(2.19, 4.07, 5.95)	4.07
	LA_{52}			
	LA_{53}			
LA_6	LA_{61}	(4.45, 5.73, 7.07)	(3.12, 4.58, 6.36)	4.69
	LA_{62}			
	LA_{63}			
LA_7	LA_{71}	(5.57, 6.50, 7, 72)	(2.78, 4.22, 6.18)	4.39
	LA_{72}			
	LA_{73}			
LA_8	LA_{81}	(4.21, 5.33, 5, 6.67)	(2.95, 4.27, 6)	4.40
	LA_{82}			
	LA_{83}			
LA_9	LA_{91}	(2.67, 4, 5.33)	(2.26, 3.8, 5.33)	3.80
	LA_{92}			
	LA_{93}			
LA_{10}	LA_{101}	(1.31, 2.47, 3.64)	(0.91, 1.97, 3.27)	2.05
	LA_{102}			
	LA_{103}			

The fuzzy lean index of the tier-one attributes has been computed using equation (1). The fuzzy lean index of the tier-one lean attributes is shown in Table 9. The weighted performance and the performance index of the tier-one lean attributes are shown in Table 9.

The overall fuzzy lean index of the company has been computed using equation (2). The computation of OFLI is given below.

$$OFLI = \frac{\begin{bmatrix} \{(2.73, 4.03, 5.34) \otimes (0.85, 0.95, 1)\} \\ \oplus\{(6.17, 7.29, 8.47) \otimes (0.7, 0.8, 0.9)\} \\ \oplus\{(5.21, 6.6, 8.03) \otimes (0.5, 0.65, 0.8)\} \\ \oplus\{(2.47, 3.67, 4.94) \otimes (0.5, 0.65, 0.8)\} \\ \oplus\{(2.58, 4.29, 5.92) \otimes (0.85, 0.95, 1)\} \\ \oplus\{(4.45, 5.73, 7.07) \otimes (0.7, 0.8, 0.9)\} \\ \oplus\{(5.57, 6.5, 7.72) \otimes (0.5, 0.65, 0.8)\} \\ \oplus\{(4.21, 5.33, 6.67) \otimes (0.7, 0.8, 0.9)\} \\ \oplus\{(2.67, 4, 5.33) \otimes (0.85, 0.95, 1)\} \\ \oplus\{(1.31, 2.47, 3.64) \otimes (0.7, 0.8, 0.9)\} \end{bmatrix}}{\begin{bmatrix} (0.85, 0.95, 1) \oplus (0.7, 0.8, 0.9) \oplus (0.5, 0.65, 0.8) \\ \oplus(0.5, 0.65, 0.8) \oplus (0.85, 0.95, 1) \oplus (0.7, 0.8, 0.9) \\ \oplus(0.5, 0.65, 0.8) \oplus (0.7, 0.8, 0.9) \oplus (0.85, 0.95, 1) \\ \oplus(0.7, 0.8, 0.9) \end{bmatrix}}$$

$$OFLI = (3.61, 4.90, 6.27)$$

The overall lean index of the company has been computed by performing an arithmetic mean operation on the overall fuzzy lean index. The computation of the overall lean index is given below.

$$OFLI = \frac{(3.61, 4.90, 6.27)}{3}$$

$$OFLI = 4.932$$

Similarly, the overall lean index of the company has been calculated using the second and third expert's responses. The overall lean indices of three experts are shown in Table 10.

Table 10 OLI of existing system

	OLI
Expert 1	4.932
Expert 2	4.847
Expert 3	4.893

The performance indices (PIs) for all tier-one lean attributes have been computed using equation (4). All lean attributes having performance index value less than 4.15 are considered to be weakly performing lean attributes. Table 11 highlights the weakly performing lean attributes and their corresponding PIs.

Table 11 PIs of tier-one lean attributes (see online version for colours)

Tier-one attributes	LA_i	PI_i	$PI_{cut\text{-}off}$
Use of space and movement of materials	LA_1	3.83	4.15
Inventory management	LA_2	5.91	
Scheduling system	LA_3	4.42	
Resource management	LA_4	2.52	
Quality control	LA_5	4.07	
Safety environment	LA_6	4.69	
Flexibility of production system	LA_7	4.39	
Management of variation	LA_8	4.40	
Maintenance	LA_9	3.80	
IoT-digitalisation	LA_{10}	2.05	

Now, as we have identified the weakly performing lean attributes. In Section 7, we will see how certain lean tools and methodologies can be utilised to identify and eliminate waste in the system.

7 Scope of lean implementation

As we have identified the weak lean attributes, root cause analysis has been performed to identify the lean wastes generated. In Figure 3, the fishbone diagram depicts the various factors contributing to the generation of lean waste-defects.

Figure 3 Fish bone diagram-defects

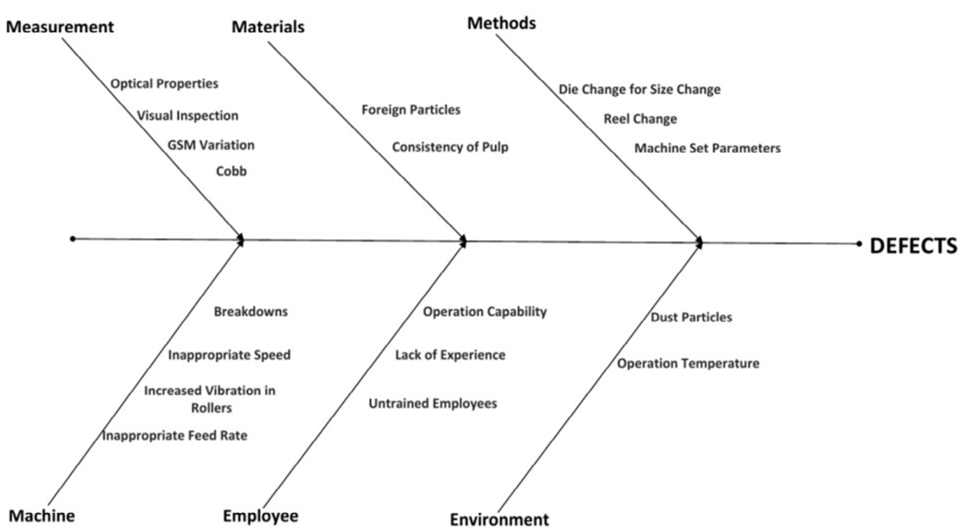
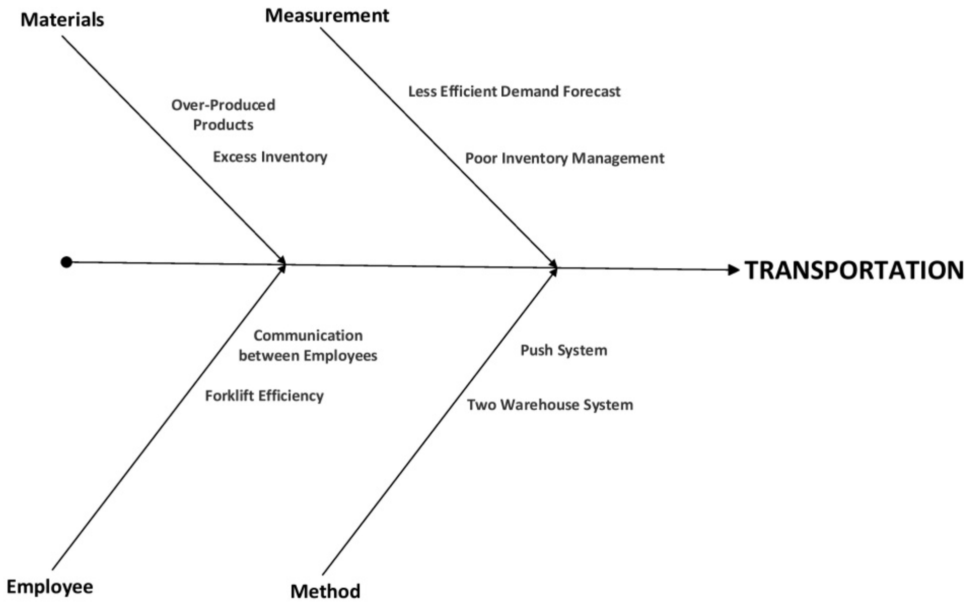
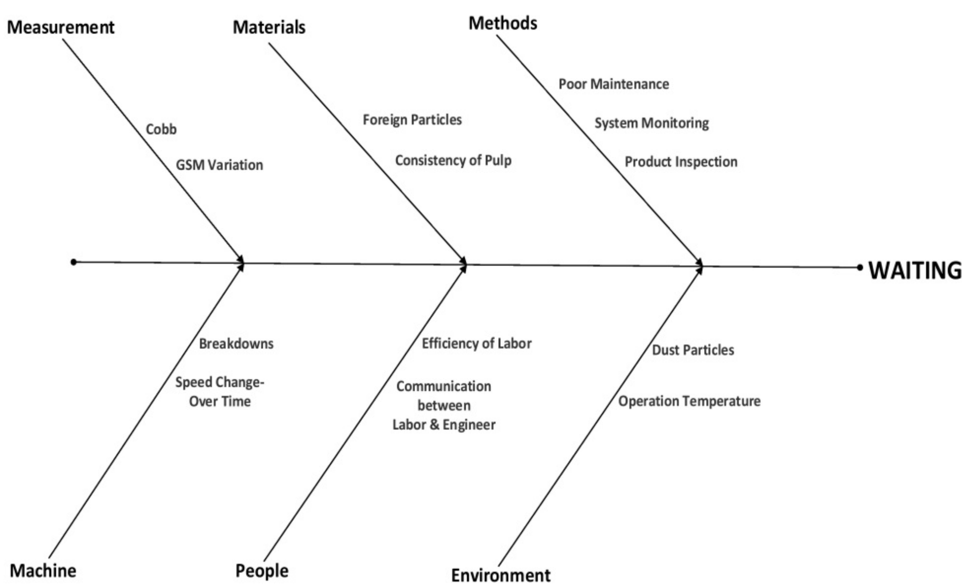


Figure 4 Fish bone diagram-transportation



Similarly, Figures 4 and 5 depicts various factors contributing to the generation of lean wastes transportation and waiting respectively.

Figure 5 Fish bone diagram-waiting



7.1 Proposed lean methodologies

Having identified the lean wastes, suitable lean methodologies have to be adopted to improve the performance of the weak lean attributes.

7.1.1 Jidoka

From the detailed study of the system, it was identified that the excess vibrations from the bearings resulted in defective products. The periodic vibration measurement system was the underlying cause of generation of defective products. To avoid defective products, a continuous vibration monitoring system has been modelled. A piezoelectric sensor has been installed which allows continuous measurement of bearing vibrations. The measured vibration values are continuously transferred to a computer system. The healthy vibration values are predefined in the system. If the bearing experiences unhealthy vibrations, the system is going to alert and stop the production immediately in order to avoid the flow of defective products. The implementation of the continuous vibration monitoring system has eventually reduced the flow of defective products and improved the work quality in the production system.

7.1.2 Single-minute exchange of die

In the sheet cutter section, paper reels are unwounded to trim the paper as per customer's size requirement. Reel changeover occurs when reel completely gets unwounded. The changeover takes over ten minutes, resulting in lean waste-waiting. An effective methodology is to be adopted in order to reduce changeover time. Instead of a single reel holder, dual reel holders can be used. The second holder will pre-engage the next reel before even the main reel completely gets unwounded, resulting in reduced changeover time. The implementation of this approach has reduced the changeover time from 10 minutes to 3 minutes.

7.1.3 Just-in-time

From the detailed study of the system, it was identified that the procured raw materials have been transported from the vendor's location and stored in two warehouses though, single warehouse is large enough to store raw materials. The utilisation of two warehouses results in double transportation of the raw materials and delay in the delivery of raw materials to the next section in the production system. This situation led to increased lead times and waste the resources needed to transport the raw materials. So, a single warehouse has to be utilised. The second warehouse is not going to be used unless space constraint is experienced in the main warehouse. The utilisation of a single warehouse has resulted in effective storage of inventory and immediate delivery of raw materials to the next section when needed. Also, the utilisation of a single warehouse has reduced the inventory levels and its carrying costs. The implementation of this system has resulted in reduced lead times and optimum inventory levels.

7.1.4 Total productive maintenance

The production system has been experiencing frequent mechanical breakdowns due to worn out bearings, high operating temperature and surface irregularities on the rollers.

These frequent breakdowns led to the generation of lean waste-waiting. Though maintenance activities have been practised, there existed a need for highly efficient maintenance methodologies to reduce the breakdowns. The implementation of total productive maintenance (TPM) could bring in the practice of preventive maintenance. Preventive maintenance aids to proactively perform periodic maintenance activities, repairs and replacements so that breakdowns can be avoided even before they happen to occur. Employees are trained for the cross-functional work environment, allowing employees to support at the different manufacturing processes. Internal quality checks are performed to assess the level of employee awareness on quality standards and benchmarks. The implementation of TPM has eventually resulted in reduced breakdowns and improved quality in the production system.

7.1.5 Kaizen

Kaizen being a productivity philosophy works to make small incremental changes in the production system. While the small incremental changes may not be noticeable over a short period of time, improvement in productivity will be experienced in the long-term. Implementation of kaizen practices will bring in employees to proactively work together and contribute to the improvements in the production system.

The detailed study of the system revealed the absence of predefined structure in practice of kaizen. So, a proper structure to practice kaizen has been formulated. Being the field workers, employees always had the privilege to get exposed to each and every process of the production system. So, ideas of improvements from employees will be more effective. Kaizen card has been utilised to enable the employees to suggest ideas of improvement. Kaizen card comprises of the problem statement, area of improvement, ideology, proposed solution and expected benefits. Top three innovative and economic ideas of improvement have been rewarded accordingly. The rewards encouraged the employees to suggest a higher number of innovative ideas for improvement. The implementation of kaizen cards resulted in an improved production system.

8 Lean assessment post-lean implementation

Lean index of the system has been computed after lean implementation to contrast the improvements made post-lean implementation. Again, three experts participated in assessing the leanness of the system. Expert's responses were recorded and lean indices have been computed.

Table 12 Detailed analysis of system post-lean implementation

Lean attributes (LA)	*Performance index (PI)*		*% improvement*
	Pre-lean	*Post-lean*	
Usage of space and movement of materials	3.83	5.25	37%
Resource management	2.52	3.46	38%
Quality control	4.07	4.56	10.5%
Maintenance	3.80	4.75	25%

Table 12 depicts the improvements shown by various tier-one lean attributes after lean implementation. For instance, the tier-one lean attribute ‘usage of space and movement of materials’ has experienced an increase in performance index from 3.83 to 5.25 accounting to 37% improvement post-lean implementation. The overall lean index of the company post-lean implementation is shown in Table 13.

Table 13 OLI of system post-lean implementation

	OLI	*% improvement*
Expert 1	5.397	9.42%
Expert 2	5.292	9.18%
Expert 3	5.304	8.39%

9 Scope of IoT implementation

In Section 6, ‘IoT-digitalisation’ was one of the identified weakly performing lean attributes. Digitalisation refers to the integration of new innovative technologies in products and processes of the manufacturing systems. IoT is utilised as a tool for digitalisation. To improve the performance of the weakly performing lean attributes, IoT models have been proposed.

9.1 Vibration monitoring system

The detailed study of the system revealed the frequent unpredicted breakdowns due to various factors such as electrical, mechanical and instrumental errors. The mechanical breakdowns owed to more than 70% of the total breakdowns. The inefficient vibration analysis on the roller bearings led to the poor surface finish of the products and unpredicted breakdowns, resulting in underutilisation of resources and machinery. So, an IoT-based continuous vibration monitoring system has been modelled. The vibration monitoring system would continuously monitor the system and alert the officials via messages and sirens if the roller bearings experience unhealthy vibrations. The implementation of this system would encourage the employees to practice productive maintenance so that breakdowns will be avoided even before they happen to occur. Also, IoT would enable the employees to monitor the system at any time from any location in the world.

9.2 Visual inspection system

In the sheet cutter section, the sheets are trimmed as per customer’s requirement. A sheet bundle will be rejected even if one of the sheets in the whole bundle appears to be defective. The defect refers to colour variations, GSM variations and poor surface finish of the sheets. To avoid defective sheets, a visual inspection system has been modelled. Highly accurate industrial cameras capable of identifying colour variations, minute dirt particles and surface irregularities inspects the sheets as it passes through the conveyor belt. If the sheet appears to be defective, a suction system will immediately suck the defective product so that the bundle remains free of defective sheets. Also, the rejection data will be stored in the system for future reference. The implementation of this system has resulted in improved work quality, customer experience and defective-free products.

Table 14 Detailed analysis of system post-IoT implementation

Lean attributes (LA)	*Performance index (PI)*		*% improvement*
	Post-lean	*Post-IoT*	
Maintenance	4.75	5.22	9.8%
IoT-digitalisation	2.05	3.68	72%

10 Lean assessment post-IoT implementation

Lean index of the system has been computed after IoT implementation to contrast the improvements shown post-IoT implementation. Again, three experts participated in assessing the leanness of the system. Expert's responses were recorded and lean indices have been computed once again. Table 15 depicts the overall lean indices of different experts post-IoT implementation.

Table 14 shows the detailed analysis of the system after the IoT implementation. In Table 14, the performance index of tier-one lean attribute 'maintenance' has increased from 4.75 to 5.22 accounting to 9.88% improvement post-IoT implementation. The IoT-based vibration monitoring system is the contributing factor for improvements experienced by tier-one lean attribute 'maintenance'.

Table 15 OLI of system post-IoT implementation

	OLI	*% improvement*
Expert 1	5.654	4.76%
Expert 2	5.632	6.42%
Expert 3	5.647	6.46%

Table 16 depicts the lean indices of various experts before lean implementation, after lean implementation and after IoT implementation. The lean indices contrast the improvements contributed by lean methodologies and IoT respectively. For expert 1, overall lean index has been increased from 4.932 to 5.397 after lean implementation and from 5.397 to 5.654 after IoT implementation. This proves evident that lean practices and IoT systems have individually contributed to the improvements in the production system. Similarly, the overall lean indices of experts 2 and 3 are shown in Table 16.

Table 16 OLI of system pre-lean, post-lean and post-IoT

	OLI		
	Pre-lean	*Post-lean*	*Post-IoT*
Expert 1	4.932	5.397	5.654
Expert 2	4.847	5.292	5.632
Expert 3	4.893	5.304	5.647

11 Conclusions

Industries have been adopting lean manufacturing for two decades. To sustain the increased competition, industries have been looking out for optimised lean models. The integration of digitalisation and lean has great potential in industrial society. Though few researchers have contributed theoretical studies implying the need for integration of lean and digitalisation in industries, there existed a need to prove it evidentially in an industry case scenario. In this paper, a case study has been conducted in a paper manufacturing company. The detailed study of the system has been conducted and VSM has been performed to identify the scope of improvement. A lean assessment model has been developed and the methodology to assess the leanness of the system also has been identified. The leanness of the system has been assessed with the aid of industrial experts. The lean assessment has been utilised to identify the weakly performing lean attributes. Root cause analysis has been performed on weak lean attributes to identify the factors contributing to the lean wastes. Suitable lean methodologies have been adopted to eliminate the lean wastes in the system. The leanness of the system has been computed post-lean implementation. IoT models have been proposed to counteract the problems faced in the production system. The leanness of the system has been computed post-IoT implementation. The lean index of the system before lean implementation, after lean implementation and after IoT implementation has been contrasted to highlight the improvements contributed by lean and IoT individually. This paper evidentially proves the need for IoT-based lean models for improved manufacturing systems.

11.1 Limitations and future scope of the study

The case study has been confined to a paper manufacturing company focusing on the integration of IoT and lean. In future, numerous numbers of studies could be conducted across various sectors such as textile, FMCG, chemical and automobile. Also, studies could be conducted on industrial implications of various digitalisation tools such as artificial intelligence, machine learning and cloud computing.

References

Bayou, M.E. and de Korvin, A. (2008) 'Measuring the leanness of manufacturing systems – a case study of Ford Motor company and General Motors', *Journal of Engineering and Technology Management*, Vol. 25, No. 4, pp.287–304.

Boyes, H., Hallaq, B., Cunningham, J. and Watson, T. (2018) 'The industrial internet of things (IIoT): an analysis framework', *Computers in Industry*, Vol. 101, pp.1–12.

Delgado, M., Verdegay, J.L. and Vila, M.A. (1992) 'Linguistic decision-making models', *International Journal of Intelligent Systems*, Vol. 7, No. 5, pp.479–492.

Hoellthaler, G., Braunreuthera, S. and Reinharta, G. (2019) 'Requirements for a methodology for the assessment and selection of technologies of digitalization for lean production systems', *Procedia CIRP*, Vol. 79, pp.198–203.

Karlsson, C. and Åhlström, P. (1996) 'Assessing changes towards lean production', *International Journal of Operations and Production Management*, Vol. 16, No. 2, pp.24–41.

Liker, J. (2004) *The Toyota Way: 14 Management Principles from the World's Greatest Manufacturer*, 1st ed., McGraw-Hill, USA.

Prinza, C., Kreggenfelda, N. and Kuhlenköttera, B. (2018) 'Lean meets Industrie 4.0 – a practical approach to interlink the method world and cyber-physical world', *Procedia Manufacturing*, Vol. 23, pp.21–26.

Rother, M. and Shook, J. (1999) *Learning to See: Value Stream Mapping to Add Value and Eliminate Muda*, Vol. 56, The Lean Enterprise Institute, Inc., Brookline, MA.

Saleeshya, P.G. and Binu, M. (2019) 'A neuro-fuzzy hybrid model for assessing leanness of manufacturing systems', *International Journal of Lean Six Sigma*, Vol. 10, No. 1, pp.473–499.

Saleeshya, P.G., Austin, D. and Vamsi, N. (2013) 'A model to assess the lean capabilities of automotive industries', *International Journal of Productivity and Quality Management*, Vol. 11, No. 2, pp.195–211.

Saleeshya, P.G., Sneha, A., Karthikeyan, C., Sreenu, C. and Rohith, A.K. (2015) 'Lean practices in machinery manufacturing industries – a case study', *International Journal of Logistics Systems and Management*, Vol. 20, No. 4, pp.536–554.

Shah, R. and Ward, T. (2003) 'Lean manufacturing: context, practice bundles, and performance', *Journal of Operations Management*, Vol. 21, No. 2, pp.129–149.

Vinodh, S. and Chintha, S.K. (2009) 'Leanness assessment using multi-grade fuzzy approach', *International Journal of Production Research*, Vol. 49, No. 2, pp.431–445.

Vinodh, S. and Vimal, K.E.K. (2012) 'Thirty criteria-based leanness assessment using fuzzy logic approach', *The International Journal of Advanced Manufacturing Technology*, Vol. 60, Nos. 9/12, pp.1185–1195.