A FUZZY LEAN SIGMA IMPLEMENTATION FAILURE RISK ASSESSMENT MODEL

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ABSTRACT-Lean Six Sigma (LSS) combines Lean manufacturing and Six Sigma into one framework. It seeks to eliminate waste, reduce process variation and improve overall value added across a production environment, with longevity as proof of its effectiveness. Risk quantification in a production setup has usually been done through traditional techniques such as Failure Mode Effect Analysis (FMEA), Monte Carlo Simulation, Decision trees, etc. No specialized approach exists for Lean Sigma manufacturing systems. This research develops a LSIFRAT(Lean Sigma Implementation Failure Risk Assessment) tool which focuses on quantifying risk in a production system that uses the Lean Six Sigma methodology. By combining fuzzy logic and the LIFRAT tool, the risk of lean six sigma implementation failure inside enterprises is measured. The input from users of a typical LSS based production system in the form of multiple indicators are measured. A sensitivity analysis was carried out to investigate different relations between the five (5) main categories of LSS indicators and the associated risk of failure under fuzzy uncertainty using a typical packaging job shop. Results showed the ability to quantify the risk of failure in a LSS system and the stage best to use LSS methods.

Keywords: Lean Six Sigma, Risk, Failure Risk assessment, Risk Quantification, Sensitivity Analysis

1.1 INTRODUCTION

Commonly referred to as Lean Six Sigma (LSS) or Lean Sigma, LSS is an integration of Lean manufacturing and Six Sigma. It combines two powerful process improvement methodologies into one framework. While the Lean strategy focuses on eliminating anything that does not add value (waste) in any process, the Six Sigma strategy focuses on design, eliminating defects, reducing process variability as well as minimizing costs (Andersson, Hilletofth, Manfredsson, Hilmola, 2014). The Six Sigma strategy gives extra value to the Lean strategy, since it squeezes out variability in time. While Six sigma provides specific statistical tools and engineering techniques for implementing changes, lean serves as the framework for waste reduction and continuous improvement.

In order to improve their businesses, organizations are now embracing this powerful tool sets to enhance competitiveness in the marketplace, increase product leadership, drive profitability, and maintain operational excellence.

Though LSS is principally employed in manufacturing, it has been adapted in various fields- government (Maleyeff, 2007); health care (Puhlman, 2016), (Dulin & Knapp, 2012); rail (Maleka et al., 2014); telecommunications (Andersson et al, 2014); law (Cook, 2015), etc. LSS tools also have a well-established reputation for eliminating waste and improving processes across several sectors, with longevity as proof of their effectiveness.

1.2 LEAN SIX SIGMA USE IN MANUFACTURING

Because Lean Six Sigma offers a more robust methodology to reducing process variation whilst minimizing waste, its application has been demonstrated by researchers in different manufacturing environments.

Venanzi (2017) used LSS to increase profitability in production system and to reduce the consumption of tools and machine optimization in the production line of an auto parts supplier company.

Ajmera et. Al (2017) adopted a structured approach in implementing LSS in a textile manufacturing firm. The textile factory's operating capacity was at a defect percentage of 8.25. On LSS implementation, the percentage defect was reduced to 2.63. There was also significant improvement in the Sigma level of the factory from 2.9 to 3.1.

Jie et. Al. (2014) developed a LSS framework for a SME label printing company. The company produces various types of labels such as computer labels, offset & silkscreen stickers and bar code labels. Using LSS, the company production capacity was shown to have an extra 896,000 impression/hour capacity in order to help the company cope with customer demands. This extra of capacity is worth two months of the current capacity in the label printing production. A significant improvement was also observed in machine in the factory, where the productivity increased from 2,709 impression/hour to 3,303 impression/hour giving an 21.93% of improvement.

Andersson, Hilletofth, Manfredsson and Hilmola (2014) developed a strategy for adopting LSS in a telecommunication manufacturing firm (Ericsson). By collecting empirical data mainly from on-site interviews and observation, an improvement project was developed to address difficulties related to delivery precision and long lead times of the company's MINI-LINK production line. The use of the LSS strategy improved flexibility, robustness, cost-efficiency, and agility of the production line at the same time.

Panat et. Al (2014) adopted the LSS methodology to systematically eliminate waste and improve the existing process of Intel's configuration control during the development and ramp phases. Results show an efficiency improvement exceeding the target (60% reduction in idle time and waste) against a target of 40% reduction. The results also showed an increase in the stakeholder satisfaction without compromising the technical rigor of the manufacturing configuration control.

As a way of implementing LSS in a food safety system to minimize risk, improve productivity and quality of products, and reducing unnecessary waste and time, Zhen (2011) applied LSS tools to minimize physical, chemical and biological hazard contamination probability in frozen salmon processing.

1.3 RISKS AND UNCERTAINTY IN LEAN SIX SIGMA APPLICATION TO INDUSTRIAL OPERATIONS

1.3.1 Risk and Uncertainty In Manufacturing

Risk according to Berk and Kartal (2012) is defined as the potential for unexpected consequences of an activity. It implies future uncertainty about deviation from an expected outcome. Various attempts have been made to quantify risks and uncertainty in manufacturing operations.

In analyzing risk and uncertainty in manufacturing processes, Aqlan and Lam (2015) calculated the total risk score of a company involved in high-end server manufacturing. Results show that for the two main product types produced by the company, risks are assessed and aggregated per product type. With the individual and combined risk scores, decision makers can perform top-down or bottom-up risk analysis and attend to the significant risks that could impress business operations.

Aqlan and Ali, (2014) assessed risk in the chemical industry by integrating lean principles and fuzzy bow-tie analysis. The risk factors dependability and influence were categorized and the risks prioritized using risk priority matrix. Risk mitigation strategies were selected using a LSS tool -Failure Mode Effect Analysis (FMEA). Fuzzy estimates are obtained for the risk factors and bow-tie analysis was used to calculate the aggregated risk probability and impact. Results showed that the proposed framework can effectively improve the risk management process in the chemical industry.

In modelling the enterprise level risks faced by an equipment manufacturer, Daultani (2017) mapped the risk parameters related to functional divisions into a Bayesian network model. Each risk parameters were represented in terms of parent and root nodes. In order to determine the probabilities of existing nodes in a Bayesian network, a methodical approach was developed to focus on obtaining the conditional probabilities of the nodes with multiple parents. A developed enterprise level value chain risk measure was used to evaluate the feasible risk states in terms of an aggregate risk number.

Guo (2016) proposed a new risk assessment methodology which uses a combination of intuitionistic fuzzy sets (IFSs) and evidence theory to analyze the potential failure modes. The risk factors S, O, and D were evaluated by using linguistic variables and intuitionistic fuzzy numbers, which were then mapped into the basic probability assignment functions. The Jousselme distance is used to compute the weights of decision makers in order to effectively group unrelated evidence. The weighted average of evidence is obtained and the classical Dempster's combination rule is used to merge the mass functions modified.

In order to effectively formulate maintenance strategies, Peter et al (2015) proposed a new risk assessment methodology which derives generic selection criteria for Failure Mode Effect Analysis, Fault Tree Analysis and Bayesian Network based on the risk assessment process outlined in the ISO 31000:2009 standard. Using the Analytic Network Process (ANP), the criteria are then prioritized taking into account expert opinion. The results show the use of the proposed methodology in helping maintenance workers identify the relevant competencies in an organization.

Also, Brustbauer (2014) analyzed enterprise risk in small and medium-sized enterprises (SMEs). The results imply that SMEs follow either an active or a passive ERM approach, which affects their strategic orientation; a passive approach denotes a defensive strategy while an active approach connotes an offensive strategy.

Betty et al. (2014) used the Fuzzy Analytic Network Process (FANP) method to assess risks involved in implementing an Enterprise Resource Planning (ERP) system in a typical production environment. Based on the results of the FANP method, the lack of management support and assistance was noted as a risk in ERP implementation. The authors surmised that top management attention and involvement is a key factor to the success of a firm's ERP implementation. Ineffective communication with users was also found to be the second highest risk factor.

Kumar and Srikanta (2014) studied the risks involved in a manufacturing supply chain. The risks were identified via brainstorming sessions, categorized as delivery performance, process capability, demand and supply fluctuation at supplier end, rework, and business practices. The FMEA analysis was used to rank the impact of all the relevant risks associated with various risk categories. The degree of impact of each relevant risk was obtained and used to infer managerial insights. Via Pareto analysis, results inferred that top 20% risk factors came from supplier and organization domain while no risk related to customer appeared in the top 20%.

1.3.2 Measuring Risks In Lean Six Sigma Systems

According to the ISO/IEC 31010, there are 31 risk assessment techniques. This listing of risk management tools and techniques is codified by The International Organization for Standardization and The International Electrotechnical Commission (IEC). These techniques including Monte Carlo, Delphi technique, FMEA, Event tree analysis, Decision tree, Markov, etc. are used interactively with other methodologies to measure and quantify risk. Their usage depends on the nature of risk being measured and area of application. Abedi, Mousakhani, Hamidi (2009), Faisal et. al (2015), Al-Gunaid et. al (2016), Vodenicharova (2017) and many more have used these methods extensively.

As stated by Reijns (2010), essential factors are necessary for successful LSS implementation, otherwise the process stands the risk of failure. Factors including managerial support, implementation approach, employee training, workers motivation (Reijns, 2010), and skill level of the LSS project team (Hilton and Sohal, 2012) are requisite to the achievement of stated LSS improvement results. It is thus evident that there exists a probability of failure when these factors are not properly addressed. Hence, there is a clear gap for an assessment tool that captures the potential failure of the LSS methodology. Deif and Mostafa (2016) introduced the Lean Implementation Failure Risk Assessment Tool (LIFRAT) as a way of measuring the probability of failure in a lean organization. This tool is based on fuzzy logic approach and it measures the risk of failure imposed by lean implementation.

Based on the LIFRAT approach, this work proposes a new model which considers the Lean Six Sigma methodology as against Lean only. This approach known as the Lean Sigma Implementation Failure Risk Tool (LSIFRAT), focuses on measuring the potential for failure in a system adopting the LSS methodology by using the LIFRAT framework.

2. THE LEAN SIGMA IMPLEMENTATION FAILURE RISK (LSIFRAT) MODEL

As identified by Deif and Mostafa (2016), sources of failure in implementing lean are categorized into four categories. These are functional, human, managerial and external factors. As a component of the LSS methodology, another factor which considers the type of LSS awareness, training and certification levels of employees in the organization is introduced. The identified factors are

a. Functional factors which account for LSS variables that involve operations and performance.
b. Human factors represented by LSS variables that describe workers' attitude and the organizational culture.
c. Managerial factors described by variables related to management at all levels.
d. External factors which are variables associated with all activities and processes beyond the control of the company e.g. government, suppliers, etc.
e. Learning factor which measures the level of LSS awareness, training and certification of employees.

Model Parameters

Let the Functional factors denoted by F
Human factors denoted by H
Managerial factors denoted by M
External factors denoted by E
Learning factor denoted by L

The overall risk of failure associated with the LSS implementation is the fuzzy sum of the risks from each factor. i.e

$$R = \sum (F + H + M + E + L)$$

In order to fully consider the influence of the LSS methodology, an in-exhaustive list of indicators for each factor mentioned above are compiled. However, due to the large number of indicators, a few ones were selected. The final step in developing the tool was to design the logic of the risk assessment tool. Fuzzy logic is chosen to use for building the logic. The fuzzy system comprised of three stages

i. Input: Four main lean variables identified earlier.
ii. Processing: Fuzzy Rules.
iii. Output: Risk of failure of lean implementation

The indicators for each factor of LSS are summarized in the table below.

Functional factors	**Human factors**	**Managerial factors**	**External factors**	**Learning factor**
Production Stability	Staff Culture	Leadership stability	Government related	LSS training
Pull and Push	Staff engagement	Learning organization	Sales force ability	Employee Certification
Standardization	Team development	Top down guidance	System stability	LSS Awareness

				level
Visual control	Staff satisfaction and stability	People motivation	Market forces	
		Customer focus	Suppliers and partners	

Table 1: A List of LSS Indicators

It is important to note that these indicators can be expanded to include many others. In order to avoid complexity, care is taken to adopt the above stated ones for this work.

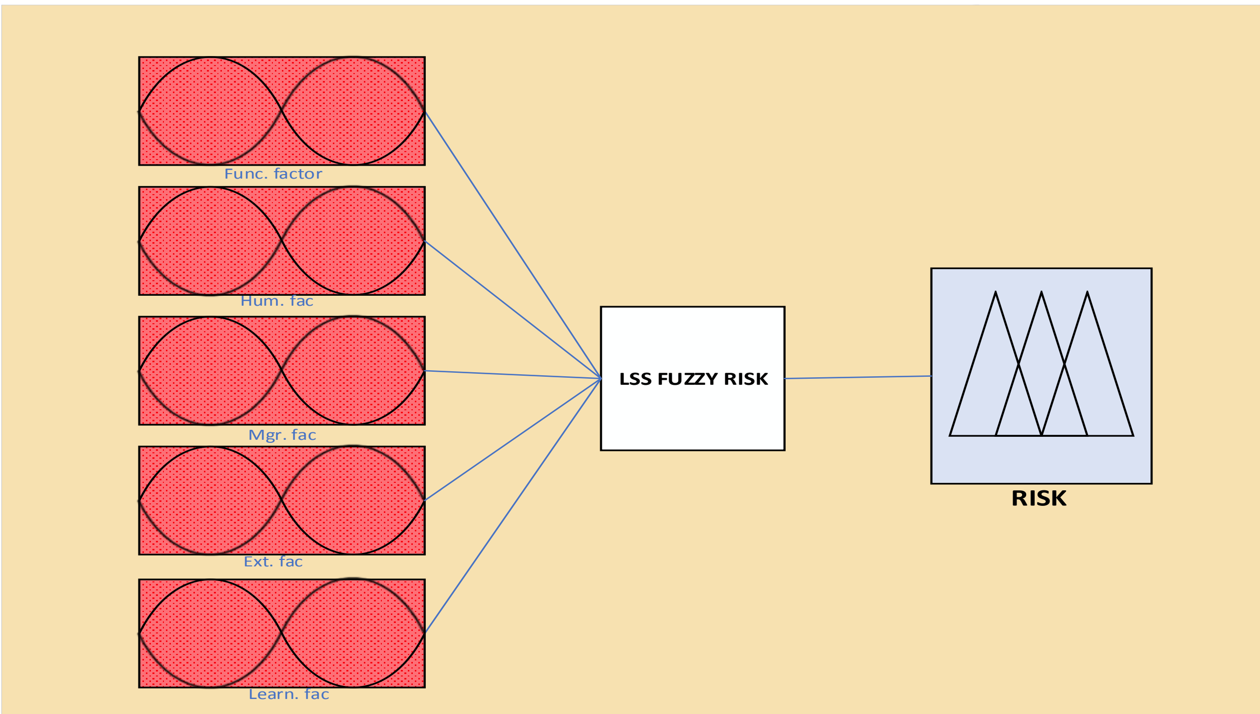

Fig 1: A Description of The LSIFRAT Model

Using SIMULINK®, a fuzzy logic system for LSIFRAT was developed as shown in Figure 1. The five identified variables of lean are denoted by F, H, M, E, and L. The value of a variable is calculated from the sum of indicator values assigned to that variable. Each variable value goes into the fuzzy block associated with it. This block holds the fuzzy rules that regulates the measurement of the risk level. The risk block is the final stage of calculating risk level. The risk calculation is composed of three stages.

Level 1: LSS Fuzzy Risk block computes the risk of LSS implementation failure based on the summed input coming from the prior stage (level 2). It contains the fuzzy rules that calculate risk calculation using input values.

Level 2 : Comprises of five blocks (F, H, M, E, and L), with each one calculating the value of the variable associated with it. F block calculates Functional factor variable's value, H block calculates Human factor variable's value, M block calculates Managerial factor variable's value, E block calculates External factor variable's value and L block calculates Learning factor variable's value. Each block calculates the associated values based on the inputs from the prior stage (level 3). Each block contains the relevant rule set that calculates the associated variable value based on the block input.

Level 3: The Simulated input for variables' indicators is defined. Each of the five variables (F, H, M, E, L) has indicators that are needed to calculate its value. Each one of these indicators should be handled as separate variable with fuzzy block and fuzzy rule set to calculate it value accurately. For simplicity, the output value of this stage is simulated as direct values (saved as vectors) to the next stage (level 2) omitting fuzzy calculations in (level 3).

3. SENSITIVITY ANALYSIS

A sensitivity analysis is performed in order to gain understanding of the developed model. Hypothetical data from a medium-sized packaging company is used for this work.

The analysis is carried out on the five variables constituting the risk model and it is limited to the first level of the model (these five variables) in order to keep the analysis simple.

The developed tool measures the risk of LSS implementation failure quantitatively and describes it qualitatively for better understanding. The tool measures two types of variables: input variables (F, H, M, E, L) and output variable (LSS Risk). In order to assign input variable values, the lifecycle of an organization is assumed to consist of four stages- Conception, Grow, Mature, and Decay during which LSS risk failure differs. Hence, the need to assume high, normal, and low input variable values. The description of the variable values is High (Value of 0.9), Normal (Value of 0.5) and Low (Value of 0.2).

	CONCEPTION	GROW	MATURE	DECAY
F	High	High	Normal	Low
H	High	Normal - High	Normal - High	Low
M	Normal	Normal	High	Low
E	Low	Normal - High	Normal - High	Low
L	Normal	Normal - High	High	Low

Table 2: The LSIFRAT Variables at each stage of the organization's lifecycle

Table 2 above identifies different levels for each of the considered variables at every stage of the company's life. Based on these scenarios, a plot of the calculated LSS risk at each phase in the cycle

Figure 3 plots the calculated risk at the different stages of the company's life cycle based on the different variables scenarios in table 2.

Figure 4. Risk of lean implementation failure associated with the company's life cycle

SUMMARY

LSS is being applied in different organizations, whether production or service-based. It has proven great results in improving the performance inside them. LSS process faces many difficulties and challenges that could lead to the failure of the implementation process. This risk of failure of the implementation process needs to be identified and measured. The LSS implementation failure risk assessment tool (LSIFRAT) was developed to measure the expected risk of lean implementation failure in a specific enterprise using fuzzy logic.

The analysis of the different scenarios for lean implementation at the different stages of a company's life cycle was conducted to determine, in a general sense, which stage of the "Business life cycle" is the best to implement lean principles. LSIFRAT will also help the company to determine in a quantitative way the risk level the company will face when implementing LSS in present time. LSIFRAT does not measure the impact and usefulness of lean implementation, nor the degree of leanness inside the company. Results show that it is easier and less risky to start LSS implementation at growth phase as in growth phase, H level is normal or high, M level is normal, F level is high, E level is normal. The results show that the highest risk to start that implementation/transformation is at decline phase as in decline phase, H level is low, M level is low, F level is low, and E level is low or normal.

Results of the sensitivity analysis results also suggest that some factors are more critical to the lean implementation process and dominate other parameters. The most important and critical factor is managerial aspects, in most cases, managerial variable dominates other variables and affect the overall risk of lean implementation failure.

REFERENCES:

1. Sadegh Abedi, Morteza Mousakhani, Naser Hamidi (2009). Using Markov Chain to Analyze Production Lines Systems with Layout Constraints. Journal of Industrial Engineering 3(2009)15-23
2. Al-Gunaid, O., Shcherbakov, M., Kamaev, V., Gerget, O., & Tyukov, A. (2016). Decision trees based fuzzy rules. Information Technologies in Science, Management, Social Sphere and Medicine, 502-508.
3. Faisal Aqlan, Sarah S. Lam (2015). A fuzzy-based integrated framework for supply chain risk assessment, International Journal of Production Economics, Volume 161, 2015, Pages 54-63, ISSN 0925-5273, https://doi.org/10.1016/j.ijpe.2014.11.013.
4. Faisal Aqlan, Ebrahim Mustafa Ali, (2014). Integrating lean principles and fuzzy bow-tie analysis for risk assessment in chemical industry, Journal of Loss Prevention in the Process Industries, Volume 29, 2014, Pages 39-48, ISSN 0950-4230, https://doi.org/10.1016/j.jlp.2014.01.006.
5. Roy Andersson, Per Hilletofth, Peter Manfredsson, Olli-Pekka Hilmola (2014). Lean Six Sigma strategy in telecom manufacturing. Industrial Management & Data Systems. Vol. 114 No. 6, 2014. pp. 904-921.
6. Berk, C. and Kartal, C. (2012). Determining major risk factors in construction projects from the view point of life cycle and stakeholder. International Journal of Business and Management Studies, Vol. 4 No. 2, pp. 11-20.
7. Betty Chang, Chin Kuo, Chih-Hung Wu, Gwo-Hshiung Tzeng, (2015). Using Fuzzy Analytic Network Process to assess the risks in enterprise resource planning system implementation, Applied Soft Computing, Volume 28, 2015, Pages 196-207, ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2014.11.025.
8. Brustbauer, Johannes. (2014). Enterprise risk management in SMEs: Towards a structural model. International Small Business Journal 34. 10.1177/0266242614542853.
9. Peter Chemweno, Liliane Pintelon, Adriaan Van Horenbeek, Peter Muchiri (2015). Development of a risk assessment selection methodology for asset maintenance decision making: An analytic network process (ANP) approach, International Journal of Production Economics, Volume 170, Part B, 2015, Pages 663-676, ISSN 0925-5273
10. Daultani, Y., Goswami, M., Vaidya, O.S. (2017). Inclusive risk modeling for manufacturing firms: a Bayesian network approach. Journal of Intelligent Manufacturing (2017). https://doi.org/10.1007/s10845-017-1374-7.
11. Faisal KP, Falah Ummer, Hareesh K C, Munavir Ayaniyat, Nijab K, Nikesh P, Jibi R (2015). Application of FMEA Method in a Manufacturing Organization focused on Quality, International Journal of Engineering and Innovative Technology (IJEIT), Volume 4, Issue 7, January 2015
12. Guo, Jian. (2016). A risk assessment approach for failure mode and effects analysis based on intuitionistic fuzzy sets and evidence theory. Journal of Intelligent & Fuzzy Systems. 30. 869-881. 10.3233/IFS-151809.
13. Roger John Hilton and Amrik Sohal (2012). A conceptual model for the successful deployment of Lean Six Sigma. International Journal of Quality & Reliability Management Vol. 29 No. 1, 2012 pp. 54-70
14. John Maleyeff, (2007). Improving Service Delivery in Government with Lean Six Sigma. Strategy and Transformation series, www.businessofgovernment.org.
15. Johnathon L. Dulin, Ashlee N. Knapp (2012). Enhancing lean six sigma methodologies with operations research tools and models: A Case Study in Healthcare.

16. Kumar Pradhan Sudeep, Routroy Srikanta, (2014). Analyzing the supply chain risk issues for an Indian manufacturing company, Journal of Advances in Management Research, Vol. 11 Issue: 2, pp.144-162, https://doi.org/10.1108/JAMR-11-2012-0047
17. Laura L. Cook, (2015). A Lean Six Sigma Framework for designing legislation.
18. Joshua Chan Ren Jie, Shahrul Kamaruddin and Ishak Abd Azid, (2014). Implementing the Lean Six Sigma Framework in a Small Medium Enterprise (SME) – A Case Study in a Printing Company. Proceedings of the 2014 International Conference on Industrial Engineering and Operations Management, Bali, Indonesia, January 7 – 9, 2014
19. Rahul Panat, Valentina Dimitrova, Tamil Selvy Selvamuniandy, Kazuhiko Ishiko, Dennis Sun, (2014). The application of Lean Six Sigma to the configuration control in Intel's manufacturing R&D environment. International Journal of Lean Six Sigma Vol. 5 No. 4, 2014 pp. 444-459
20. Rajat Ajmera, Prabhuling Umarani, and K.G.Valase (2017). Lean Six Sigma Implementation in Textile Industry, International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395 -0056 Volume: 04 Issue: 04 | Apr -2017 www.irjet.net p-ISSN: 2395-0072
21. Ramakrushna Padhy, (2017) "Six Sigma project selections: a critical review, International Journal of Lean Six Sigma, Vol. 8 Issue: 2, pp.244-258, https://doi.org/10.1108/IJLSS-06-2016-0025.
22. T.J.F. Reijns (2010). The advantages and limitations of Lean Six Sigma in process redesign. Tilburg University
23. Maria Vodenicharova (2017). Opportunities for the applications of FMEA Model in logistics processes in Bulgarian enterprises Logistics & Sustainable Transport, Vol. 8, No. 1, May 2017, 31–41. doi: 10.1515/jlst-2017-0003.