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RELIABILITY BASED MODELLING FOR FAILURE ANALYSIS IN MILK PROCESS INDUSTRY

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Abstract: *The suggested hybridized framework offers a paradigm for performance optimization-reliability-based analysis of milk processing unit's (MPU) failure behavior in the dairy industry. The proposed hybridized framework led to the development of fuzzy Jaya Based Lambda-Tau (JBLT) technique-based mathematical model for computing various performance parameters of the under-consideration unit. The availability of the system drops by 0.044% as the level of uncertainty or spread level increases from ± 15% to ± 25% and drops to 0.088% as the level of uncertainty increases from ± 25% to ± 60%. To corroborate the system's availability downward trend, the results of JBLT approach were compared with Particle Swarm Optimization-Based Lambda-Tau (PSOBLT) and conventional Fuzzy Lambda-Tau (FLT) techniques. The analysis findings were given to the maintenance manager so they could create the best maintenance schedule for the considered plant.*

Key words: *Dairy industry, fuzzy, JBLT, availability, failure analysis, maintenance schedule.*

1. Introduction

Globalization has drastically altered the industrial climate over the previous two decades. With developments in technology, and increasing system complexity; the role of reliability and maintainability in industry has intensified, making the work of reliability/system engineers more difficult (Garg et al., 2012). For this, many researchers have already established decision making techniques (Kumar, Garg, et al., 2022; Rawat et al., 2022; Pant et al., 2022) and to sustain the reliability of modern systems to a greater extent, these systems must have the optimal design or exceptionally reliable components (Garg et al., 2014). It becomes increasingly

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important when perishable dairy-based foods items like milk, cheese, curd, as well as other milk products are produced and must be delivered on time.

The dairy-based foods have seen an enormous growth in consumption due to their significant role in a balanced diet (García-Burgos et al., 2020). Among different dairy-based foods, milk is an important part of any balanced diet. Figure 1 shows the different process stages for processing of milk production. It is prepared by collecting raw milk in storage tank and then feeding raw milk into milk silo through the chiller. It is stored into milk silo at 5^0C and after that pumped to balance tank. Thereafter the milk processing includes: filtration; pasteurisation; cream separation and product-specific processing; and then pasteurized milk taken into storage tank; then packaging and after that stored in cold storage room. Figure 1 shows the schematic diagram of MPU.

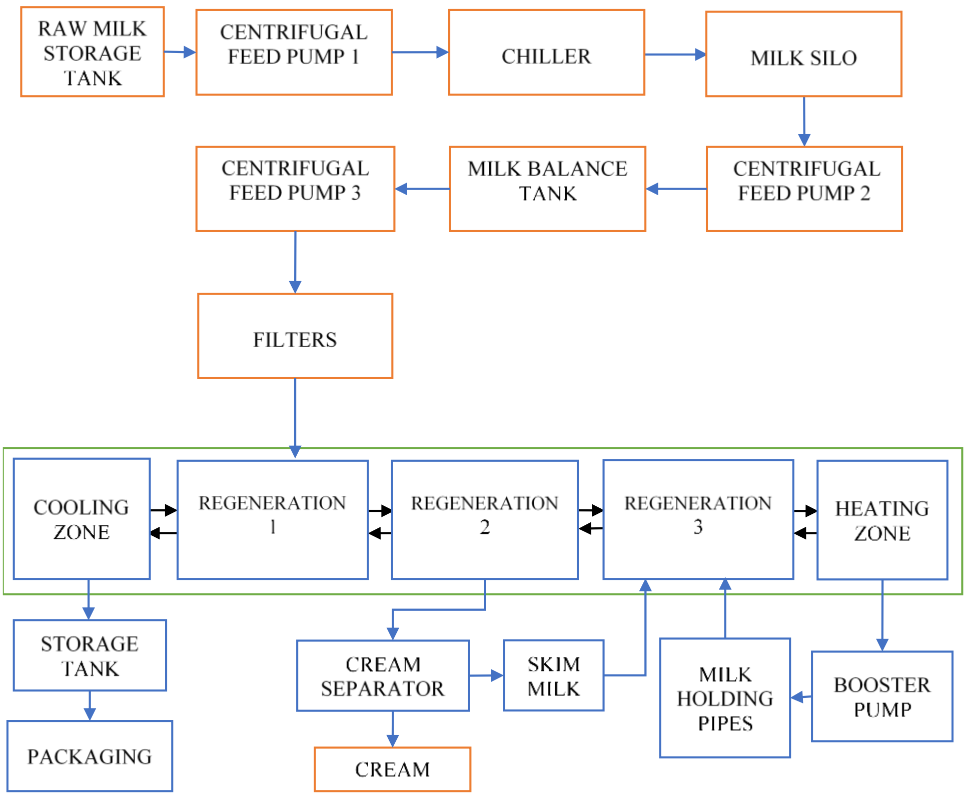


Figure 1. Schematic diagram of MPU

The sustainability of the milk industry, in turn, generates employment. Milk needs to be processed and sent to the market timely in order to turn a profit. Since milk is a perishable good, if it is not pasteurized right away, it turns sour, requiring more effort to turn into cheese-like goods, and the day's milk goal won't be accomplished (Gopal & Panchal, 2022). This would mess up the milk product supply chain, which would not only reduce overall plant profitability but also cause major brand image issues. Therefore, all subsystems and components must be in an operational state continuously for the uninterrupted supply of milk products. But failure in industrial systems, however, is an inevitable phenomenon, resulting either decrease in their operational capacity or complete failure (Komal & Sharma, 2014). A survey of 600 distinct process industries in Europe found that maintenance costs range from 15 to 40 percent of overall production costs, depending on the business (Wang et al., 2007). It is imperative to reduce or eliminate unexpected plant failures to reduce maintenance costs, and this can only be accomplished by creating an ideal maintenance policy. Hence, optimizing the performance concerns of MPU in terms of reliability is therefore of utmost importance in light of the challenges of high running expenses and satisfying the customer's demand at the appropriate time. Considering the above factors, our motivation in this work is to present a framework that includes a non-linear mathematical concept-based optimization model in terms of reliability analysis that will be useful for social and economic aspects. Earlier, many researchers have already used Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) algorithm. The benefits and drawbacks of these innovative optimization algorithms are given in table 1 (Rao, 2016).

Table 1. Benefits and drawbacks of innovative optimization algorithms

Algorithm	Benefits	Drawbacks
GA	➢ Every optimization issue that the chromosome encoding may be used to represent can be resolved by it. ➢ It finds various ways to address problems.	➢ A genetic algorithm cannot always be relied upon to find the global optimum. ➢ Numerous algorithmic-specific factors must be tuned.
PSO	➢ Like other heuristics, PSO is a formulaic approach. ➢ Possess the ability to remember.	➢ Adjustments of numerous algorithm-specific parameters are necessary.
ABC	➢ Being able to browse local searches	➢ Requires adjusting of parameters like bee, onlooker, etc.

To overcome the drawbacks of GA, PSO and ABC algorithm, JBLT approach has been proposed. The framework is presented with its application of MPU in the milk process industry. Thus, to accurately assess the failure dynamics of the considered MPU, the current work proposes a novel metaheuristic optimization technique for reliability analysis.

2. Literature background

Many researchers have already established reliability-based model for many process industries. During the modelling there are numerous diverse uncertainties that might be random and non-randomly classified. Both sorts of uncertainty can arise from complex systems (Garg & Rani, 2013). Therefore, in order to make successful decisions, the quantification of uncertainty in the analysis of reliability is important (Chaube et al., 2018; Shakshi et al., 2022; Niksirat & Nasseri, 2022). To accommodate uncertainty during the assessment of a system's reliability, a fuzzy-theoretic method has been applied by Knezevic & Odoom, (2001). Sharma et al. (2007) applied a well-organized fuzzy concept-based performance evaluation framework and was expounded with a paper mill case study. Triangular Membership

Function (TMF) was used to account the uncertainty in the collected raw data from numerous sources. S. P. Sharma et al. (2010) applied FLT approach for evaluating the various reliability parameters to assess the performance concerns of a repairable complex multi-robotic system. Garg & Sharma (2012) analysed the failure behaviour of chemical fertilizer plant where uncertainty of the collected raw data was considered using TMF. Panchal & Kumar, (2014) applied FLT modelling for carrying the reliability examination of compressor unit in a medium size power industry based on coal. Panchal et al. (2019) used FLT approach for performance optimization of chemical industry. Gopal & Panchal, (2021) applied FLT approach-based framework for analyzing the reliability indices of milk plant.

The results obtained using the fuzzy-theoretic technique or fuzzy arithmetic operations are linear in nature. Because reliability expressions (failure rate, repair time, availability) are very nonlinear and complicated in nature in most application scenarios. As a result, if fuzzy arithmetic operations were utilised throughout the analysis, it will have large levels of uncertainty in between them and hence, will not reflect the accurate behaviour of the system. To overcome this drawback of linear fuzzy models, non- linear optimization-based approach have proven to be highly effective. Kumar, Negi, et al., (2021)used Grey Wolf Optimization (GWO) and Cuckoo Search Algorithm (CSA) for minimizing the cost by taking availability as constraints for butter oil processing system. Kumar, Vohra, et al. (2021)expounded use of various optimization techniques for petroleum engineering. Furthermore, in the past non-linear concept-based reliability approaches have been developed by Garg & Rani, (2013); Komal et al. (2010); Wu et al. (2011); Garg et al. (2012); Sharma et al. (2012); Pant et al., (2017); Kumar, Pant, et al., (2022); Uniyal et al. (2022); Gopal & Panchal, (2023).

Although, these approaches have proved worthwhile for giving highly accurate results which depends upon the consideration of fine-tuning algorithmic-specific parameters. The common control factors can be adjusted, but the algorithm-specific factors are unique to GA, PSO and ABC algorithm only (Rao, 2016). To overcome this problem, Jaya Algorithm (JA) a metaheuristic optimization technique with no algorithm-specific parameters consideration (Rao & Saroj, 2017) prove to very advantageous in terms of time intricacy when incorporated with traditional FLT approach over the existing PSOBLT approach-based model.

As a result, the objective of this study is to list the uncertainties and give a methodology for assessing the failure behaviour quickly. Therefore, for assessing the failure behavior, a structured integrated framework based is presented on MPU in a dairy industry situated in the northern province of India.

3. Proposed reliability based integrated framework

The proposed framework consists of two phases which is shown in Figure 2. Initially, data on failure and repair time was gathered in the first phase from a number of sources, including the logbook and the team of maintenance specialists. A PN model for MPU was established in the second phase to reflect its intricate series-parallel structure. TMF was also utilised to fuzzify the collected data in order to accommodate uncertainty. JA codes were developed using the innovative JBLT approach in order to simulate the top event of the PN model. The optimised reliability parameters were calculated at various spreads using the JBLT optimization approach, and then compared with PSOBLT and FLT. Figure 2 presents the proposed reliability based integrated framework.

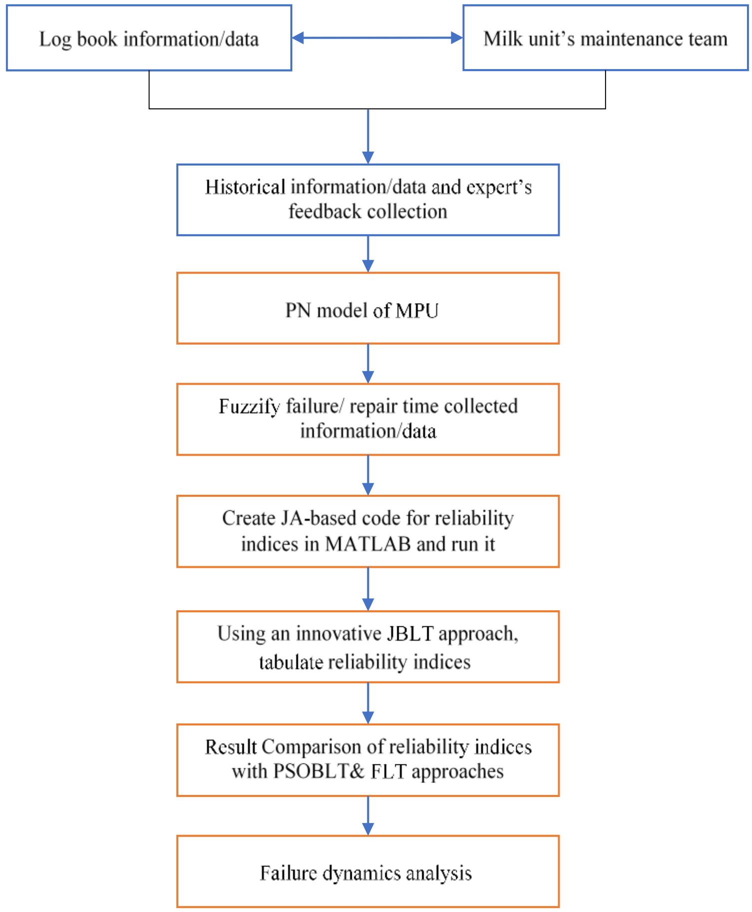


Figure 2. Reliability analysis-based framework

4. Reliability analysis-based approach

4.1. JBLT Optimization approach

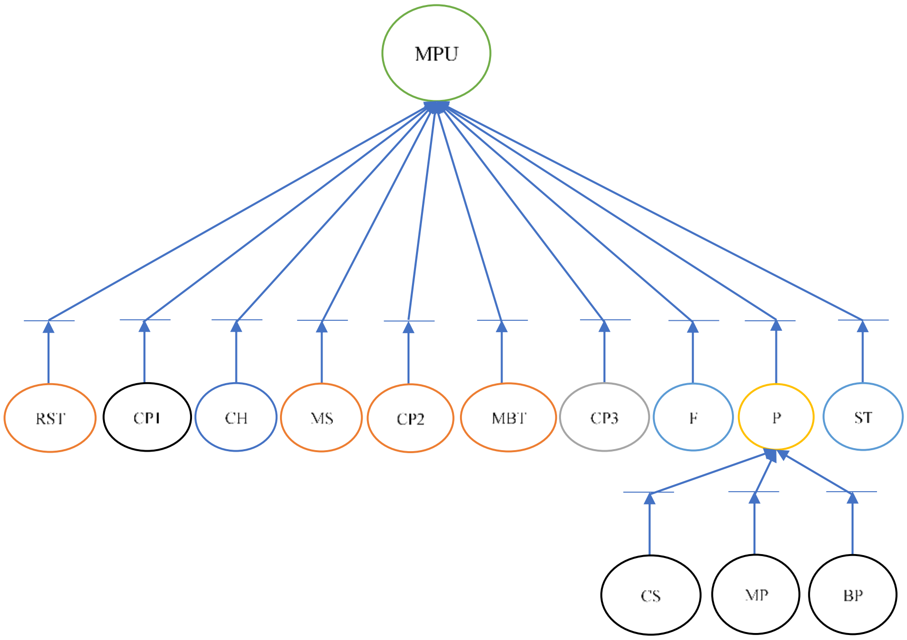
Rao RV firstly proposes this algorithm in the year 2016. In Sanskrit, Jaya means "victory," implying that the good will triumph over the evil. This approach was developed to address both constrained and unconstrained optimization issues (Rao, 2016; Rao & Saroj, 2017). For examining the failure behavior of the MPU, the Jaya Based Lambda-Tau (JBLT) optimization approach has been presented in the current research. The FLT technique is incredibly powerful when integrated with soft computing approaches and produces extremely accurate results.

The benefit of the using Jaya algorithm is that it does not need any algorithm-specific parameters, unlike PSO, which requires updating the inertia coefficient, social, and cognitive components. Such unique parameters are not necessary for this algorithm to find the optimal solution; rather, it is endeavouring to generate the optimal solution. The basic steps of JBLT optimization can be summarized as follows:

1. Develop a PN model for describing the complex series-parallel configuration of the given system.
2. Collect MPU's failure and repair time data from multiple sources, such as maintenance experts and maintenance logbooks, for various sub-systems/components represented in the PN model.
3. Fuzzify the gathered crisp failure and repair time data using TMF as stated by Đalić et al. (2020); Singh et al. (2020).
4. In MATLAB, define objective function.
5. Establish the starting population size, the variables, and the termination standards.
6. Identify the best and worst solutions.
7. Modify the solution on the basis of best and worst solutions.
8. If the solution obtained is better than earlier solution, then replace the solution; otherwise keep earlier solution.
9. If the condition for termination met, then note the optimum solution, otherwise repeat from step 6.
10. Then, compile data at various levels of reliability parameters.
11. To transform obtained values into crisp values, use the Center of Area (COA) expression.

5. Reliability analysis-based results

A PN model for the MPU was developed using a series-parallel configuration, as shown in Figure 3. The equipment like raw milk storage tank, centrifugal pump (1), chiller, milk silo, centrifugal pump (2), milk balance tank, centrifugal pump (3), filters, pasteurizer, and storage tank are in series configuration. Cream separator, milk holding pipes, and booster pump are in series configuration with pasteurizer as shown in Figure 3.



Where, MPU: Milk processing unit, RST: Raw milk storage tank, CP-1: Centrifugal pump, CH: Chiller, MS: Milk silo, CP-2: Centrifugal pump, MBT: Milk balance tank, CP-3: Centrifugal pump, F: Filters, P: Pasteurizer, CS: Cream separator, MP: Milk holding pipes, BP: Booster pump, ST: Storage tank

Figure 3. Milk processing unit's PN model

For each equipment/component of the unit, failure and repair time data were gathered from the plant's maintenance expert and maintenance log book available in plant maintenance department and are shown in Table 2.

Table 2. Failure and repair time data

Component	Failure Rate (Failures/hr)	Repair time (hrs)
Raw milk storage Tank (n = 1)	4.629×10^{-4}	4
Centrifugal feed Pump (n = 2)	3.472×10^{-4}	2
Chiller (n = 3)	2.311×10^{-4}	2
Milk silo (n = 4)	2.311×10^{-4}	3
Centrifugal feed Pump (n = 5,7)	3.472×10^{-4}	2
Milk balance tank (n = 6)	1.16×10^{-4}	2
Filter (n = 8)	1.388×10^{-3}	1
Pasteurizer (n = 9)	2.311×10^{-4}	8
Cream separator (n = 10)	3.472×10^{-4}	4
Milk holding pipes (n = 11)	2.228×10^{-4}	5
Booster pump (n = 12)	4.629×10^{-4}	2
Storage Tank (n = 13)	3.472×10^{-4}	1

For accounting the fuzziness of the obtained failure and repair time data, Triangular Fuzzy Number (TFNs) are calculated at various spreads (±15%, ±25%, ±60%) (Knezevic & Odoom, 2001). Expressions for the top event's failure rate (λ_s) and repair time (τ_k) are constructed and given as:

$$\lambda_s = \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 + \lambda_7 + \lambda_8 + \lambda_9 + (\lambda_{10} + \lambda_{11} + \lambda_{12}) + \lambda_{13} \quad (1)$$

$$\begin{aligned}\tau_s &= (\tau_1\lambda_1 + \tau_2\lambda_2 + \tau_3\lambda_3 + \tau_4\lambda_4 + \tau_5\lambda_5 + \tau_6\lambda_6 + \tau_7\lambda_7 + \tau_8\lambda_8 + \tau_9\lambda_9 + \ldots \\ &\ldots\tau_{10}\lambda_{10} + \tau_{11}\lambda_{11} + \tau_{12}\lambda_{12} + \tau_{13}\lambda_{13}) / (\lambda_s)\end{aligned} \quad (2)$$

A JBLT optimization approach-based modeling function (equation 3) was developed using MATLAB coding, with a mission time of t = 168h.

Maximize/Minimize:

Maximize/Minimize:

$$\tilde{F}(\lambda_1,\ldots,\lambda_j,\tau_1,\ldots,\tau_k) \text{ or } \tilde{F}(t/\lambda_1,\ldots,\lambda_j,\tau_1,\ldots,\tau_k) \quad (3)$$

Subject to:

$$\mu_{\lambda_a}(x) \geq \alpha$$

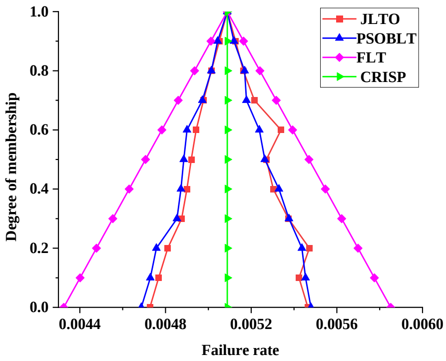
$\mu_{\tau_b}(x) \geq \alpha$, where $0 \leq \alpha \leq 1$

$$a = 1,2\ldots, j$$

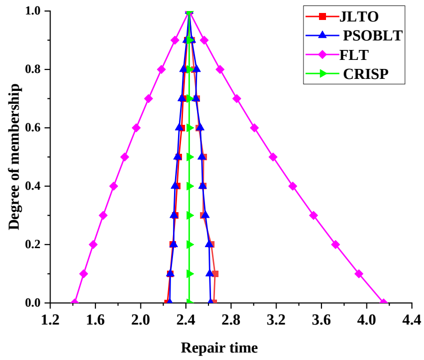
$$b = 1,2\ldots, k$$

Where $F(\lambda_1,\ldots,\lambda_j, \tau_1,\ldots\ldots\tau_k)$ are time-independent reliability functions; and $F(t/\lambda_1,\ldots,\lambda_j, \tau_1,\ldots\ldots\tau_k)$ are time-dependent reliability functions.

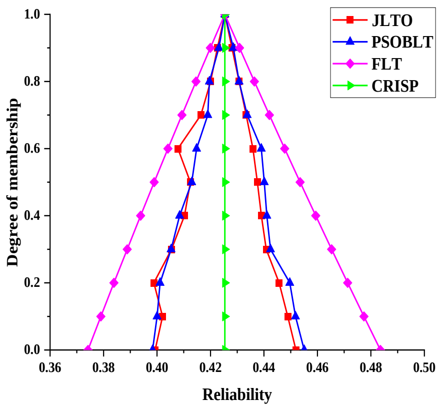
Using equations 1 and 2 in equation 3, optimized values for reliability indices were tabulated at varied α cut (between 0-1) for different spreads. Here, in MATLAB coding, parameters like population size are randomly taken (Garg & Rani, 2013; Singh et al. 2020). The best results from 30 different simulations run were chosen for all reliability indices to minimize stochastic disparity. Fig. 4(a-e) shows trends of various reliability indices at ±15% spreads. The results of various reliability indices are closer to crisp value with the implementation of JBLT and PSOBLT in comparison to FLT approach.


JLTO
PSOBLT
FLT
CRISP
Degree of membership
1.0
0.8
0.6
0.4
0.2
0.0
0.0044
0.0048
0.0052
0.0056
0.0060
Failure rate

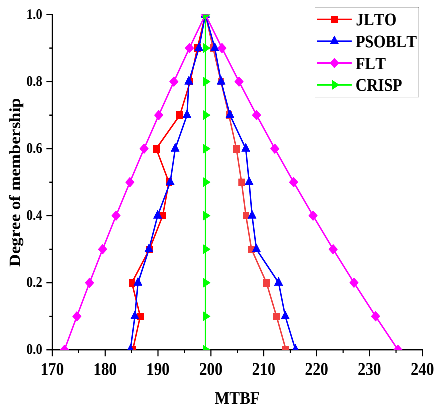
(a)


JLTO
PSOBLT
FLT
CRISP
Degree of membership
1.0
0.8
0.6
0.4
0.2
0.0
1.2
1.6
2.0
2.4
2.8
3.2
3.6
4.0
4.4
Repair time

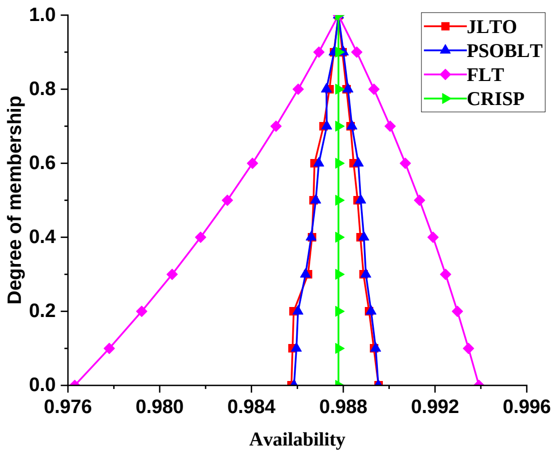
(b)


JLTO
PSOBLT
FLT
CRISP
Degree of membership
1.0
0.8
0.6
0.4
0.2
0.0
0.36
0.38
0.40
0.42
0.44
0.46
0.48
0.50
Reliability

(c)


JLTO
PSOBLT
FLT
CRISP
Degree of membership
1.0
0.8
0.6
0.4
0.2
0.0
170
180
190
200
210
220
230
240
MTBF

(d)



(e)

Figure 4(a-e) Trends of reliability indices at ±15% spreads

Table 3 shows reliability parameters values obtained using COA expression so that their increasing/decreasing trends can be examined.

Table 3. Reliability parameters values obtained by JBLT, PSOBLT, FLT

Spread	Approach	Failure rate	Repair time	MTBF	Reliability	Availability
±0 %	Crisp	0.005088	2.429	198.96	0.425361	0.987791
Defuzzified values						
±15 %	JBLT	0.0050933	2.438	199.46	0.42554	0.987689
	PSOBLT	0.0050846	2.435	199.91	0.426245	0.987725
	FLT	0.0050882	2.665	202.21	0.427695	0.986000
±25 %	JBLT	0.0051444	2.483	198.61	0.42277	0.987251
	PSOBLT	0.0051060	2.465	200.04	0.42545	0.987449
	FLT	0.0050882	3.133	208.40	0.43186	0.982452
±60 %	JBLT	0.0051261	2.537	209.42	0.43147	0.986386
	PSOBLT	0.0050319	2.476	213.33	0.43792	0.987020
	FLT	0.0050882	10.369	280.60	0.46348	0.933096

The results achieved using the new JBLT optimization approach are compared with well-known FLT (Panchal et al., 2019) and PSOBLT (Garg & Rani, 2013) approaches and the resulting comparison is shown in table 3.

6. Results Discussion

Table 3 shows that under JBLT approach when the spread raised from ± 15% to ± 25% system's failure rate increased to 1.003%; repair time increased to 1.846%; MTBF decreased to 0.426%; reliability decreased to 0.651%; availability decreased to 0.044%. Similar when the spread increased from ± 25% to ± 60%, system's failure rate decreased to 0.356%; repair time increased to 0.446%; MTBF increased to 5.443%; reliability increased to 2.058%; availability decreased to 0.088%.

Furthermore, under PSOBLT approach application, system's failure rate increased to 0.421%; repair time increased to 1.232%; MTBF increased to 0.065%; reliability decreased to 0.186%; availability decreased to 0.028% when the spread raised from ± 15% to ± 25%. Likewise, when spread increased from ± 25% to ± 60%, i.e. system's failure rate decreased to 1.451%; repair time increased to 0.446%; MTBF increased to 6.644%; reliability increased to 2.931%; availability decreased to 0.043%.

Also, under traditional FLT technique when the spread raised from ± 15% to ± 25%, no change in failure rate was observed, repair time increased to 17.561%, MTBF increased to 3.061%, reliability increased to 0.974%; availability decreased to 0.36%. Similarly, when spread increased from ± 25% to ± 60%, i.e. no change in system's failure rate; repair time increased to 230.96%; MTBF increased to 34.645%; reliability increased to 7.322%; availability decreased to 5.024%.

From the above-discussed results, most of the reliability parameters like failure rate, repair time, reliability and availability show similar increasing/decreasing trends with the implementation of JBLT and PSOBLT optimization approaches at spread ± 15% to ± 25% and ± 25% to ± 60%. On the other hand, with the implementation of traditional FLT approach at spread ± 15% to ± 25%, failure rate shows no change, reliability shows increasing trend irrespective of trend observed with JBLT and PSOBLT. Furthermore, at spread ± 25% to ± 60%, failure rate shows no change, irrespective of trend observed with JBLT and PSOBLT. Since system availability, one of the primary performance parameters, exhibits a decreasing trend with the implementation of all approaches, it is essential to conduct a risk analysis of the considered MPU in order to increase system availability over the long term.

7. Conclusion

To address the quantitative performance concerns, creative framework for analyzing MPU has been presented. A novel fuzzy JBLT optimization approach was created and put into use to optimize the reliability indices of MPU. To account for uncertainty and ambiguity, the fuzzy set notion was applied. Results from the widely used non-linear PSOBLT and FLT techniques were evaluated with those of the JBLT approach. Results show that the availability of the MPU unit declines as uncertainty rises for all reliability evaluation techniques. Under JBLT approach when the spread raised from ± 15% to ± 25%, availability decreased to 0.044% and then further decreased to 0.088% when spread increased from ± 25% to ± 60%,. Under PSOBLT and FLT approach when the spread raised from ± 15% to ± 25%, availability decreased to 0.028% and 0.36%. Then further decreased to 0.043% and 5.024% when spread increased from ± 25% to ± 60%, Since, one of the key performance indicators, system availability, demonstrates a downward tendency with the implementation of all techniques, it is vital to undertake a risk analysis of the MPU that is being examined to improve availability of MPU over the long run.

7.1 Managerial implications

The proposed framework, which uses quantitative methods to optimize the reliability indices of the MPU, will benefit plant maintenance professionals as:

- To analyze, and foresee the behavior of MPU with more practicality.
- To design appropriate maintenance strategies.

- To reduce operating and maintenance costs.

7.2 Limitations of the work

The outcome may be impacted if the quality of the expert feedback is poor because the fuzzy set theory used in the current framework depends on it. As a result, the information supplied by experts directly affects the output outcomes. Another drawback of the approach is that hesitation and indeterminacy were completely absent, whereas fuzzy set theory takes vagueness and ambiguity in the raw data into consideration. Since the results are based on a constant failure rate model, the interdependence between the numerous equipment/components is not present.

7.3 Future scope of the work

For reliability analysis, Weibull distribution could be employed to account for the interdependence of multiple components. Additionally, a new mathematical modeling framework might be created by including the intuitionistic fuzzy set notion, and the results may be contrasted with those generated using the suggested framework. Furthermore, integrated framework using metaheuristics with multi criteria decision making (MCDM) could be developed so that failure based risky component can be identified. The proposed integrated approach could be used to analyze performance issues of various real industrial systems related to different process industries like spinning mill, bottling plant, soft drink plant, food processing industries etc.

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Conflicts of Interest*:* The order of authors mentioned in the title page is final to best of our belief. We declare that there is no conflict regarding authorship.

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