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A STRUCTURED FRAMEWORK FOR RELIABILITY AND RISK EVALUATION IN THE MILK PROCESS INDUSTRY UNDER FUZZY ENVIRONMENT

Nand Gopal, Dilbagh Panchal

Department of Industrial and Production Engineering,
Dr B R Ambedkar National Institute of Technology Jalandhar, Punjab, India

Abstract. *This paper aims at proposing a novel integrated framework for studying reliability and risk issues of the curd unit in a milk process industry under uncertain environment. The considered plant's complex series-parallel configuration was presented using the Petri Net (PN) modeling. The Fuzzy Lambda-Tau (λ-τ) approach was applied to study and analyze the reliability aspects of the considered plant. Failure dynamics of the curd unit has been analyzed with respect to increasing/ decreasing trends of the tabulated reliability indices. Availability of the considered plant shows a decreasing trend with an increase in spread values. For improving the system's availability, a risk analysis was done to identify the most critical failure causes. Using the traditional FMEA approach, the FMEA sheet was generated on the basis of expert's knowledge/experience. The Fuzzy-Complex Proportional Assessment (FCOPRAS) approach was applied within FMEA approach for identification of critical failure causes associated with different subsystem/components of the considered plant. In order to check the consistency of the ranking results, the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) was applied within the FCOPRAS approach. Ranking results are compared for checking consistency and robustness of critical failure causes related decision making which would be useful in designing the finest maintenance schedule for the considered curd unit. Overheating/moisture lead to winding failure ($MSCP_5$), visible sediment of milk jam in filter ($MBFP_3$), improper quality of oil (H_4), blade breakage (CTK_4), wearing in gears (PFM_{11}), and cylinder leakage (CFM_7) were recognized as the most critical failure causes contributing to system unavailability. The analysis results were supplied to the maintenance manager for framing a suitable time-based maintenance intervals policy for the considered unit.*

Key Words: *Milk Process Industry, Lambda- Tau, Reliability, FMEA, FCOPRAS, FTOPSIS*

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Corresponding author: Nand Gopal
Department of Industrial and Production Engineering, Dr B R Ambedkar National Institute of Technology Jalandhar, Punjab, India - 144011
E-mail: nandgopal504@yahoo.co.in

1. INTRODUCTION

Dairy milk products are an emerging food industry in the world. At present, the Indian government faces an immense pressure to overcome the issues of youth unemployment. Milk process industries are of supreme importance for overcoming this issue as these industries heavily depend upon the rural people because of their dependency on agriculture and dairy sectors. Dairy based food products such as curd, ghee, ice-cream and cheese, etc. are big contributors to a balance diet and due to this, their consumption has increased to manifold [1]. Curd is one of the important dairy products which is a semi-solid product obtained from the pasteurized milk by souring, using bacterial cultures. It is prepared by feeding milk received from the chiller, stored into storage tank at 5^0C and pumped to balance tank. Then, it passes through heat exchanger (pasteurizer) where the temperature of milk is raised to 45^0C - 50^0C, and then it is subjected to homogenization. Homogenization is done at 2000 to 2500 psi to mix all ingredients thoroughly. After that, it again passes through the heating zone of the heat exchanger where the temperature is raised to 90^0C. Then, it is pumped to the holding tank through the booster pump and the milk from the holding tank enters to the cooling zone where heat exchange takes place and milk temperature is reduced to 45^0C - 50^0C. Further, the milk enters different culture tanks where it is cooled to 40^0C - 45^0C; then culture is added and pouch/cup filling takes place in the specified section. The milk is further held at 43°C in the incubation room where fermentation of curd is done and the curd is cooled at below 5°C in order to stop the fermentation process in the cold store room.

The curd processing unit in milk process industries consists of a large number of subsystem/components arranged in series/parallel configuration. Any failure in these subsystem/components will lead to a production loss; besides, plant will not be able to meet the customer demand on time. For such type of complex configuration-based units' failure is an inescapable phenomenon which results in a heavy operational loss. To overcome the issue of operational loss, reliability of subsystem/components should be at top priority. As per the survey in Europe for heavy process industries, it is the maintenance cost which contributes nearly 15 percent to the total production cost [2]. Minimization of this percentage by designing and implementing an optimum maintenance policy could directly result in reducing the total operational cost, which means bigger profit to the considered industry.

For the development of optimal maintenance policy, correctness of analysis result is of supreme importance. Crisp set theory based integrated framework has been already developed and applied by many researchers for studying failure behavior of various complex industrial system. These frameworks consider only crisp data obtained from different sources, which has an element of uncertainty in input data results in biased results responsible for poor maintenance schedule. For developing optimum maintenance schedule, it is essential to study and analyze the qualitative and quantitative failure behavior of the complex systems with the consideration of uncertainty in the input data. Therefore, to deal with this challenge, performance analysis in terms of reliability and risk analysis under uncertainty is highly important for correct evaluation of failure behavior of the considered complex system for which application of the Fuzzy Methodology (FM) with in performance evaluation tool is of supreme importance. Thus, the current work presents a novel Fuzzy Methodology (FM) based structured framework utilizing MCDM approaches for analyzing the performance in terms of reliability and risk analysis under uncertainty for correct evaluation of failure behavior of the considered complex system.

2. LITERATURE BACKGROUND

Reliability and risk analysis are regarded as a noteworthy sustainable prerequisite for any process industry. Therefore, all the working equipment must be available for full-time so that maximum productivity can be achieved. For that, it is very essential to maintain the performance of subsystem/components in terms of reliability and risk. Milk plant curd unit needs to be evaluated to uphold its high availability. From the available literature, it has been noted that a number of researchers have done work in the direction of studying stochastic failure behavior of real complex industrial systems in terms of reliability and risk parameters. Researchers were motivated to develop different mathematical techniques based structured framework and resources to analyze reliability and risk parameters. For instance, Aggarwal et al [3] developed a mathematical model based on the Chapman-Kalmogorav Birth-Death method for tabulating reliability parameters in order to study performance issues related to skim milk powder system in a dairy plant. Gowid et al [4] applied time dependent Markov methods based on crisp set theory to obtain the reliability parameters results for production plant of LNG. The Markovian model so implemented in the above reported work considering crisp data only means it does not consider uncertainty/vagueness in the raw data/information collected from experts. Therefore, an element of uncertainty persists with the results obtained from the Markovian model. To overcome this drawback fuzzy methodology-based approaches gained strength and were implemented by various researchers in different work.

Knezevic and Odoom [5] developed a fuzzy λ-τ approach to address failure dynamics of the repairable system under uncertainty. Gupta et al [6] suggested fourth order Runge - Kutta method for measuring the system's reliability. Aksu et al [7] proposed a technique for reliability assessment that complements Failure Mode Effect Analysis (FMEA), Fault Tree Analysis (FTA) and Markov analysis and illustrated it with application in the propulsion system of the pod. Qiu et al [8] combined probabilistic and non-probabilistic methodology to find the bounds of system's structural reliability. Sharma et al [9] developed structural framework by using the Fuzzy Methodology (FM) which is valuable for the plant maintenance manager to envisage the behavior of system. Sharma et al [10] used the Genetic Algorithms (GA) based λ-τ method to compute reliability measures of paper mill. Zhang et al [11] applied a method of extended the Grey Relational Analysis (GRA) to solve Multi Criteria Decision-Making (MCDM) problems with triangular fuzzy numbers valued at intervals with an example of hiring a system analysis engineer for software company. Durmić et al [12] applied the Full Consistency Method (FUCOM) and the Rough Simple Additive Weighting (SAW) methods to obtain criteria weights for sustainable supplier selection. Bozanic et al [13] proposed integrated FUCOM – Z-number – Multi-Attributive Border Approximation Area Comparison (MABAC) approaches based framework for the selection of command post location. Badi and Pamucar [14] presented grey theory-based Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) approaches based model for selecting the best supplier in a Libyan iron and steel industry. Kishore et al [15] proposed Analytic Hierarchy Process (AHP) – SAW approaches for the selection of sub-contractors. Vesković et al [16] applied fuzzy based PIvot Pairwise RElative Criteria Importance Assessment (PIPRECIA) method for finding individual importance of each criteria in the selection of reach stacker based handling facility. Chatterjee and Chakraborty [17] developed a meta-model for obtaining technological value of cotton fiber. Maity et al [18] implemented grey COPRAS approach for the selection of tool material so as to enhance the machining performance. These MCDM approaches are found to be very useful in solving the decision problem of different areas. Considering the importance of these approaches, many authors make use of these approaches in studying the reliability and risk analysis of real industrial systems. Sharma et al [19] proposed GA based fuzzy λ-τ method to calculate different reliability parameters of the washing system in paper industry. Deveci et al [20] applied the FMEA approach to evaluate potential errors in the cutting process of electric cable. Garg et al [21] expounded an artificial bee colony-based Lambda-Tau (ABCBLT) hybridized methodology to analyze butter-oil processing plant reliability indices. Panchal and Kumar [22] carried out reliability analysis of Compressor house unit (a subsystem of thermal power plant) using λ-τ approach. Fuzzy λ-τ approach and Fuzzy FMEA approach were also implemented to study and analyze the performance issues of chlorine gas plant in a chemical process industry [23]. In the above reported work, the authors developed reliability and risk parameters based structured framework, which consider MATLAB toolbox software-based analysis. In the MATLAB toolbox software-based analysis IF-THEN rules are generated and for effectivity of analysis results common IF-THEN rules are required to be eliminated. The elimination of common IF-THEN rules is a difficult task for the analyst and due to this problem biasness in the analysis results still persists. Also, consideration of equal weightage to three risk factors under this approach raises serious concern related to accuracy of ranking results. To overcome these limitations, there is a gap for a novel integrated framework for studying the reliability and risk issues under uncertainty in an unbiased manner. To bridge this gap, a novel FM based structured framework utilizing MCDM approaches has been proposed in this work and is presented with its application on the curd unit in the milk process industry located in northern part of India. The flow chart for the proposed structured framework is presented in Fig. 1.

In the proposed framework, firstly, a reliability analysis was carried out in which failure and repair time data collected from maintenance logbook integrated with maintenance experts was used. PN modeling as per series-parallel arrangement of the considered unit was done. Further, crisp raw data of considered unit were converted into a fuzzified form for considering the vagueness of the collected information and reliability indices were tabulated at different spreads (± 15%, ± 25%, ± 60%). Output values were converted into crisp form and reliability indices-based failure behavior of the considered unit was studied and analyzed as per increase/decrease trends. In the second phase, for enhancing the system's availability, a risk analysis was carried out. For that, using the FMEA approach risky failure causes investigation was carried out for the listed failure causes under different subsystem/components. Risk factors, namely, occurrence (O_f), severity (S) and detection (O_d) probability, relationship was obtained from maintenance experts and their weights were calculated by using a fuzzy extent analysis method. MCDM approaches, namely, FCOPRAS and FTOPSIS were implemented and on the basis of their output scores each listed failure cause was ranked. The ranking results were further compared for an effective and intelligent decision-making related to their criticality which contributes to the system's unavailability.

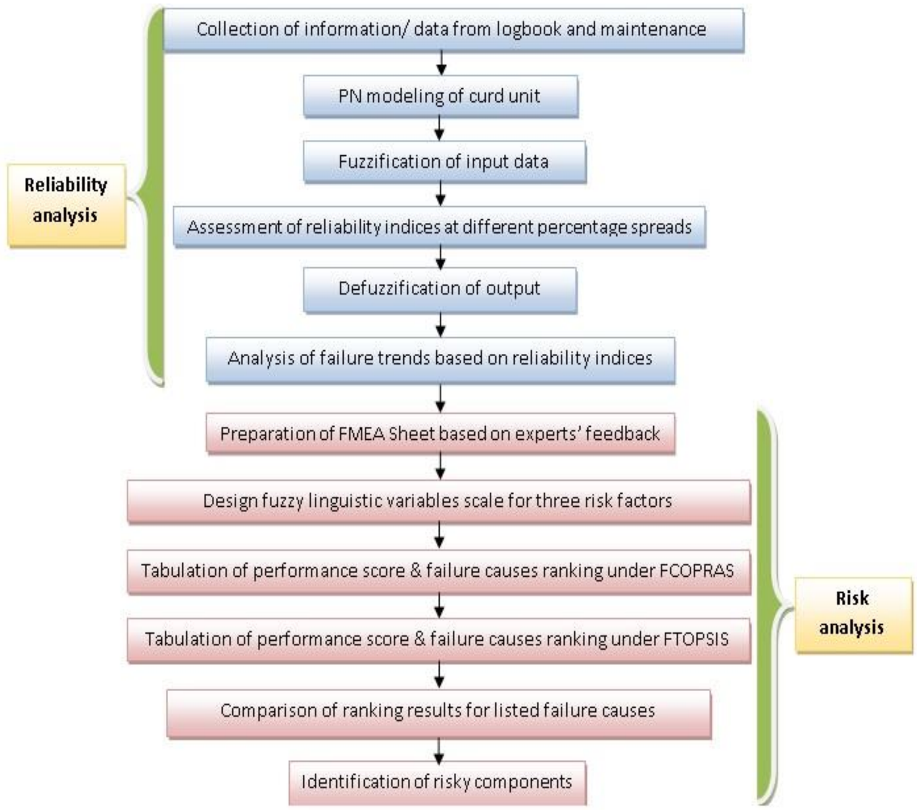

Fig. 1 Proposed framework flow chart

3. Fuzzy Concept, Reliability and Risk Modeling Based Approaches

3.1. Notions of the fuzzy set theory

This section only deals with those fuzzy concepts which were used in the proposed framework [22].

3.1.1. Crisp and fuzzy set

A cisp set is defined as grouping of elements $x \in X$ that are countable and finite; where each element can either belong to or not belong to the set.

In 1965, Zadeh introduced the theory of the fuzzy which can be defined as [22]:

$$\mu_{\tilde{A}}(x): U \rightarrow [0,1] \quad (1)$$

where U represents the universe of discourse and $\mu_{\tilde{A}}(x)$ is membership function of x in $\tilde{A}$ fuzzy set.

3.1.2. Membership function (MF)

In the literature, different forms of MF such as triangular, trapezoidal, Gaussian, piecewise linear and singleton, etc. have been used by different researchers to consider vagueness in the collected information [22, 23]. Many researchers were extensively using triangular Membership Function (TMF) in the past to consider uncertainty/vagueness in the collected data/information for carrying reliability and risk analysis for real industrial systems [21, 24, 25]. In the present work, TMF is used because of its easiness in computation. A TMF is defined mathematically as:

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x-R}{S-R}, R \le x \le s \\ 1, x = s \\ \dfrac{T-x}{T-S}, S \le x \le T \\ 0, otherwise \end{cases} \tag{2}$$

3.1.3. Linguistic variables

Linguistic variable means a variable whose values are words/sentences in a natural/artificial language. It is tough/hard to suggest a justified definition, which states the intricacy of the problems. So, these variables are beneficial for collecting views in many circumstances and could accept words from usual language, which are then well-expounded by a fuzzy set in the range recommended by variables [26].

3.2. Reliability and MCDM approaches

3.2.1. Lambda- Tau (λ-τ) approach

Fuzzy λ-τ approach is a powerful tool for evaluating reliability parameters under uncertainty developed by Knezevic and Odoom in 2001 [5]. Since then, this approach has been widely implemented by various researchers for studying the failure behavior of different complex industrial systems based on tabulated reliability parameters at different spreads. Since the fuzzy λ-τ approach considers uncertainty in raw data (provided by experts) which is one of the main limitations of the already existed Markovian approach, the so-obtained analysis results with the implementation of the fuzzy λ-τ approach are highly effective in terms of accuracy. Due to this advantage, the fuzzy λ-τ approach has been applied by many researchers in different process industries like paper mill, thermal power plant, and urea fertilizer industry, etc. [21, 23]. Various steps of the fuzzy λ-τ approach are discussed as follows:

Step 1: Use AND/OR gate develop PN model for representing series-parallel complex arrangement of the considered system.

Step 2: Collect failure and repair time data of different subsystem/components as represented in PN model from various sources, namely, maintenance experts and maintenance logbook, etc.

Step 3: Using TMF as defined by Eq. (2), fuzzify the collected crisp failure and repair time data related to each sub-system/component.

Step 4: Using AND/OR gate transition expressions for series-parallel arrangement as shown in Table 1, develop mathematical modeling for the top event of the PN model.

Table 1 Basic expression of λ-τ methodology [5]

Gate	λ_{AND}	λ_{OR}	τ_{AND}	τ_{OR}
Expressions	$\prod_{j}^{n}\lambda_j\left[\sum_{i=1}^{n}\prod_{\substack{j=1\\ i\neq j}}^{n}\tau_j\right]$	$\sum_{i=1}^{n}\lambda_i$	$\dfrac{\prod_{i=1}^{n}\tau_i}{\sum_{j=1}^{n}\left[\prod_{\substack{i=1\\ i\neq j}}^{n}\tau_i\right]}$	$\dfrac{\sum_{i=1}^{n}\tau_i\lambda_i}{\sum_{i=1}^{n}\lambda_i}$

The developed mathematical equations for AND/OR gate transition from the basic expression (Table 1) are represented as:

AND gate transition expression [5]

$$\lambda^{\alpha}=\begin{bmatrix}\prod_{i=1}^{n}\{(\lambda_{i2}-\lambda_{i1})\alpha+\lambda_{i1}\}.\sum_{j=1}^{n}\left[\prod_{\substack{i=1\\ i\neq j}}^{n}\{(\tau_{i2}-\tau_{i1})\alpha+\tau_{i1}\}\right], \\ \prod_{i=1}^{n}\{-(\lambda_{i3}-\lambda_{i2})\alpha+\lambda_{i3}\}.\sum_{j=1}^{n}\left[\prod_{\substack{i=1\\ i\neq j}}^{n}\{-(\tau_{i3}-\tau_{i2})\alpha+\tau_{i3}\}\right]\end{bmatrix} \tag{3}$$

$$\tau^{\alpha}=\left[\frac{\prod_{i=1}^{n}\{(\tau_{i2}-\tau_{i1})\alpha+\tau_{i1}\}}{\sum_{j=1}^{n}\left[\prod_{\substack{i=1\\ i\neq j}}^{n}\{-(\tau_{i3}-\tau_{i2})\alpha+\tau_{i3}\}\right]},\frac{\prod_{i=1}^{n}\{-(\tau_{i3}-\tau_{i2})\alpha+\tau_{i3}\}}{\sum_{j=1}^{n}\left[\prod_{\substack{i=1\\ i\neq j}}^{n}\{(\tau_{i2}-\tau_{i1})\alpha+\tau_{i1}\}\right]}\right] \tag{4}$$

OR Gate Transition [5]

$$\lambda^{\alpha}=\left[\sum_{i=1}^{n}\{(\lambda_{i2}-\lambda_{i1})\alpha+\lambda_{i1}\},\sum_{i=1}^{n}\{-(\lambda_{i3}-\lambda_{i2})\alpha+\lambda_{i3}\}\right] \tag{5}$$

$$\tau^{\alpha}=\begin{bmatrix}\dfrac{\sum_{i=1}^{n}\left[\{(\lambda_{i2}-\lambda_{i1})\alpha+\lambda_{i1}\}.\{(\tau_{i2}-\tau_{i1})\alpha+\tau_{i1}\}\right]}{\sum_{j=1}^{n}\left[\{-(\lambda_{i3}-\lambda_{i2})\alpha+\lambda_{i3}\}\right]}, \\ \dfrac{\sum_{i=1}^{n}\left[\{-(\lambda_{i3}-\lambda_{i2})\alpha+\lambda_{i3}\}.\{(\tau_{i3}-\tau_{i2})\alpha+\tau_{i3}\}\right]}{\sum_{j=1}^{n}\left[\{(\lambda_{i2}-\lambda_{i1})\alpha+\lambda_{i1}\}\right]}\end{bmatrix} \tag{6}$$

Step 5: Using reliability expressions as shown in Table 2, tabulate various reliability parameters for the considered mission time (t) at different α cut values varying from 0-1

Table 2 Various reliability parameters [5]

Reliability indices	Expression
Mean time to failure	$MTTF_c = \dfrac{1}{\lambda_c}$
Mean time to Repair	$MTTR_c = \dfrac{1}{\mu_c}$
Mean time between failure	$MTBF_c = MTTF_c + MTTR_c$
Availability	$A_c(t) = \dfrac{\mu_c}{\mu_c + \lambda_c} + \dfrac{\lambda_c}{\mu_c + \lambda_c} e^{-(\mu_c + \lambda_c)t}$
Reliability	$R_c(t) = e^{-\lambda_c t}$
Expected Number of failures	$ENOF = \dfrac{\lambda_c \mu_c t}{\mu_c + \lambda_c} + \dfrac{\lambda_c^2}{(\mu_c + \lambda_c)^2}[1 - e^{-(\mu_c + \lambda_c)t}]$

Step 6: Using center of area (COA) expression as represented in Eq. (7) [27], tabulate crisp values for various reliability parameters to study and analyze the failure behavior of the considered system

$$\bar{S}_0(\tilde{Y}) = \frac{\int_c^d s\beta_{\tilde{y}}(s)ds}{\int_c^d \beta_{\tilde{y}}(s)ds} \tag{7}$$

3.2.2. FMEA approach

FMEA is a widely used tool that helps in listing the failure causes, effects, and modes related with different subsystem/components of the complex industrial system [28]. A system or process may have several failure modes/failure causes and failure effects. In that condition, it is necessary to assess each failure cause and prioritize them accordingly. This approach considers the Risk Priority Number (RPN) for prioritizing failure causes; the scores for these causes are computed by multiplying O_f, S and O_d. However, the crisp RPN score based ranking results were disparaged by many researchers because of many reasons [29, 30, 31]. Significant disparaged results include:

- Different failure causes may give same RPN score.
- Equal weightage consideration for three risk factors under traditional FMEA approach.
- Consideration of only crisp values in the form of expert's feedback means consideration of uncertainty is missing.

3.2.3. Fuzzy COPRAS Method

Zavadsas and Kaklauskas, first introduced this method in 1996. It is a renowned multi attribute decision-making method for finding the most appropriate alternative among all alternatives. This method is applied vigorously in numerous disciplines of decision-making such as in critical infrastructures risk ranking [32], evaluating performance measures [33], hybrid wind farm [34], problems in selecting material [35], renewable energy sources [36], selecting maintenance strategy [37], because of its simplicity and consideration of both ideal and ideal-worst solutions [38]. It is based on characteristics of the alternatives where the characteristics are contradictory. Although characteristics and expert's decision may contain uncertainty and imprecise data, the traditional approaches are still inadequate to model complex problems. So, their deftness is enhanced by integrating fuzzy logic into this approach. In comparison to the other MCDM approaches, the COPRAS method deals with the conflicting criteria for solving the decision problem. Due to this advantage, in the present work COPRAS approach, has been incorporated within the FMEA approach for ranking the listed failure causes under three conflicting risk factors. The various steps involved in the fuzzy COPRAS approach are as follows.

Step 1: Develop the initial decision matrix $(\tilde{M})$ for the three risk factors. The developed decision matrix is mathematically represented by Eq. (8).

$$\tilde{M} = \tilde{m}_{ij} = \begin{bmatrix} \tilde{m}_{11} & \tilde{m}_{12} & \dots & \tilde{m}_{1q} \\ \tilde{m}_{21} & \tilde{m}_{22} & \dots & \tilde{m}_{2q} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{m}_{p1} & \tilde{m}_{p2} & \dots & \tilde{m}_{pq} \end{bmatrix} \tag{8}$$

where $i = 1, 2 \dots p$ and $j = 1, 2 \dots q$; $\tilde{m}_{ij} = [m_{ij}^{lb}, m_{ij}^{mb}, m_{ij}^{ub}]$ is a TFN and *lb, mb, ub* are the lower bound, middle bound and upper bound.

Step 2: Using Eq. (9), convert a fuzzified values-based matrix into a crisp values-based decision matrix.

$$m_{ij} = \frac{m_{ij}^{lb} + 4m_{ij}^{mb} + m_{ij}^{ub}}{6} \tag{9}$$

where the developed crisp values-based matrix is represented by Eq. (10).

$$M = m_{ij} = \begin{bmatrix} m_{11} & m_{12} & \dots & m_{1q} \\ m_{21} & m_{22} & \dots & m_{2q} \\ \vdots & \vdots & \vdots & \vdots \\ m_{p1} & m_{p2} & \dots & m_{pq} \end{bmatrix} \tag{10}$$

where $i = 1, 2, \dots p$ and $j = 1,2,\dots q$

Step 3: Develop a normalized decision matrix using Eq. (11).

$$\overline{m}_{ij} = \frac{m_{ij}}{\sum_{i=1}^{p} m_{ij}} \tag{11}$$

The obtained normalized decision matrix is represented as:

$$\overline{M} = \overline{m}_{ij} = \begin{bmatrix} \overline{m}_{11} & \overline{m}_{12} & \dots & \overline{m}_{1q} \\ \overline{m}_{21} & \overline{m}_{22} & \dots & \overline{m}_{2q} \\ \vdots & \vdots & \vdots & \vdots \\ \overline{m}_{p1} & \overline{m}_{p2} & \dots & \overline{m}_{pq} \end{bmatrix} \tag{12}$$

where $i = 1, 2, \dots p$ and $j = 1,2,\dots q$

Step 4: Using Eq. (13), develop a weighted normalized decision matrix

$$\hat{m}_{ij} = w_j \times \overline{m}_{ij} \tag{13}$$

where the weights for the three risk factors are calculated by using the fuzzy Extent Analysis Method [39, 40] and the developed weighted normalized decision matrix is represented by Eq. (14).

$$\hat{M} = \hat{m}_{ij} = \begin{bmatrix} \hat{m}_{11} & \hat{m}_{12} & \dots & \hat{m}_{1q} \\ \hat{m}_{21} & \hat{m}_{22} & \dots & \hat{m}_{2q} \\ \vdots & \vdots & \vdots & \vdots \\ \hat{m}_{p1} & \hat{m}_{p2} & \dots & \hat{m}_{pq} \end{bmatrix} \tag{14}$$

where $i = 1, 2, \dots p$ and $j = 1,2,\dots q$

Step 5: Calculate the sum for beneficial (BC_{+i}) and non-beneficial (BC_{-i}) criteria values by using Eqs. (15) and (16).

$$BC_{+i} = \sum_{j=1}^{q} \hat{m}_{+ij} \tag{15}$$

$$BC_{-i} = \sum_{j=1}^{q} \hat{m}_{-ij} \tag{16}$$

Step 6: Using Eq. (17), tabulate relative output significance (R_i) for listed failure causes.

$$R_i = BC_{+i} + \frac{\sum_{i=1}^{p} BC_{-i}}{BC_{-i} \sum_{i=1}^{p} \frac{1}{BC_{-i}}} \tag{17}$$

Step 7: Calculate performance scores (U_i) for each failure cause by using Eq. (18) and rank the listed failure causes in a descending order.

$$U_i = \frac{R_i}{R_{\max}} \times 100\,\% \tag{18}$$

3.2.4. Fuzzy TOPSIS

Among many MCDM approaches, the TOPSIS method, established by Hwang and Yoon in 1981, has become quite widespread owing to its simplicity, completeness and ease in results computation [17]. It is employed to get the ideal result among the similar decisions [41, 42]. This technique permits a compromise amongst several decision considerations where bad effect in any one of the factors can be balanced with the beneficial effect of other factor [43]. Since uncertainty occurs almost in all decision data the TOPSIS can be simply extended with a fuzzy set concepts for handling the vagueness/uncertainty of the raw data for high accuracy in decision results [44]. In the past, for checking the consistency of ranking results obtained from many other novel decision-making approaches, the fuzzy TOPSIS approach was integrated and found the application of integrated model in different fields [23, 45, 46, 47, 48, 49, 50]. In the present work, the FTOPSIS approach is integrated with the FCOPRAS approach for evaluating the consistency of ranking results because of its mathematical modeling similarity with many steps of the FCOPRAS approach. The first four steps of FTOPSIS are similar to the FCOPRAS approach and the remaining different steps are discussed as follows:

Step 5: Calculate ideal best solution (VV_j^+) and ideal worst solution (VV_j^-) for the three risk factors.

Here, in this work, O_f and S are considered as non-beneficial criteria, and O_d are beneficial criteria, so (VV_j^+) is calculated by taking minimum value for non-beneficial criteria and maximum value for beneficial criteria. Ideal worst solution (VV_j^-) is calculated by taking maximum value for non-beneficial criteria and minimum value for beneficial criteria.

Step 6: Tabulate the Euclidean distance from ideal best (SS_j^+) and Euclidean distance from ideal worst (SS_j^-) by using Eqs. (19) and (20) as:

$$SS_i^+ = \sqrt{\sum_{j=1}^{n}(VV_{ij} - VV_j^+)^2} \tag{19}$$

$$SS_i^- = \sqrt{\sum_{j=1}^{n}(VV_{ij} - VV_j^-)^2} \tag{20}$$

Step 7: Using Eq. (21), tabulate final performance score (FPS_i) for each failure cause and rank the failure causes in a descending order.

$$FPS_i = \frac{SS_i}{SS_i^+ + SS_i^-} \tag{21}$$

4. CASE STUDY

The proposed framework is presented with its application to the curd unit of a milk production plant located in the northern part of India. The curd unit is one of the most critical units of the considered milk process industry consisting of various subsystem/components, namely, milk storage tank, centrifugal feed pump, milk balance tank pasteurizer and culture tank, etc. which are arranged in series-parallel complex configuration as shown in Fig. 2.

The main subsystem/components of the considered unit are discussed as follows:

(i) **Milk storage tank:** used for storing milk and set in series arrangement.

(ii) **Centrifugal pump**: arranged in series configuration and used for pumping the milk from milk storage tank to balance tank.

(iii) **Milk balance tank**: It is a standardization process which is done to balance fat and solids-not-fat (SNF). It is also arranged in series configuration.

(iv) **Pasteurizer:** used to exchange the heat and has three different plates namely, regeneration-1, regeneration-2, regeneration-3 connected in series configuration with the unit.

(v) **Homogenizer:** used to reduce the formation of cream by its high pressure 2000 to 2500 psi to mix all ingredients thoroughly and arranged in series configuration with the unit.

(vi) **Booster pump:** used to pump the milk from pasteurizer to holding tank and culture tank. It is also arranged in series configuration.

(vii) **Holding tank:** arranged in series and it is used to hold the heated milk (90^0c) so that contaminates, and microbes can be killed.

(viii) **Culture tank:** used to cool down the milk up to 40^0c - 45^0c and then culture is added. For pouch filling one unit of culture tank is arranged in series configuration and for cup filling two units of culture tanks are arranged in parallel configuration.

(ix) **Pouch filling machine:** used to fill the pouch of curd and two units are arranged in parallel set up.

(x) **Cup filling machine:** used to fill the cup of curd and two units are arranged in parallel set up. One unit is operative and other remains in stand-by mode.

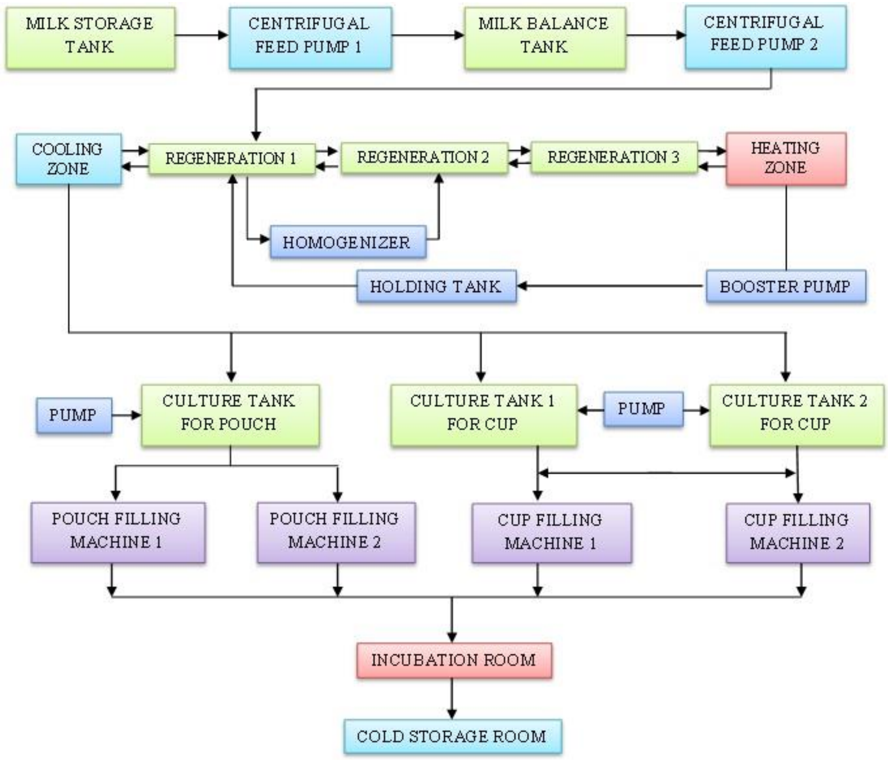

Fig. 2 Curd unit schematic diagram

4.1. Proposed framework application

4.1.1. Reliability Analysis-Fuzzy λ-τ approach application

Using AND/OR gate symbol, develop PN model (Fig. 3) representing series-parallel arrangement for the considered curd unit of the milk process industry.

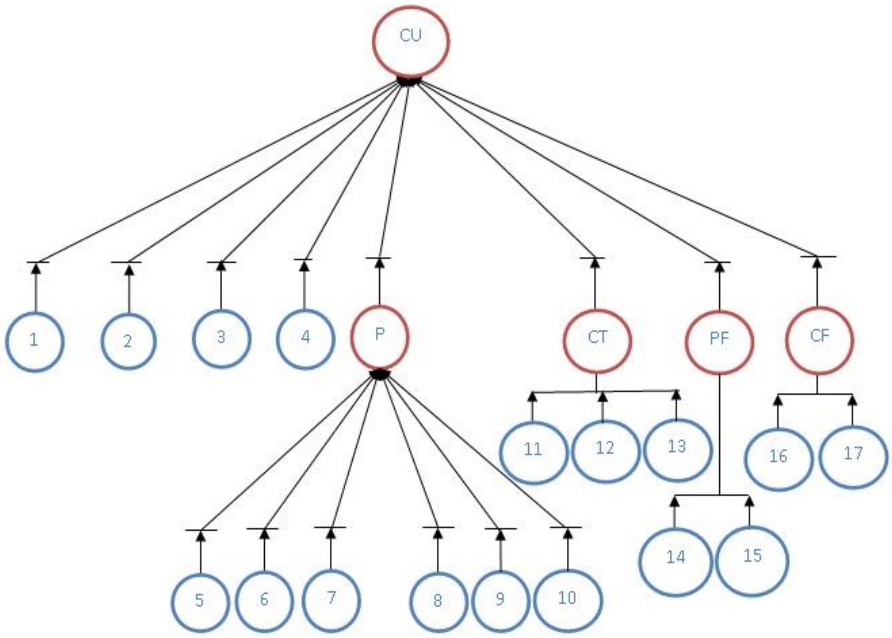

Fig. 3 PN Model

In Fig. 3: CU: Curd Unit, P: Pasteurizer, CT: Culture Tank, PF: Pouch Filling, CF: Cup Filling

On the basis of expert opinion and maintenance log book record failure rate (λ_i) and repair time (τ_i) data for each subsystem/component was collected as shown in Table 3.

Table 3 λ_i - τ_i data of considered unit

Component	Failure Rate (λ_i) (Failures/hr)	Repair time (τ_i) (hrs)
Milk Storage Tank (*n=1*)	2.31 x 10^{-4}	4
Centrifugal feed Pump (*n=2*)	3.37 x 10^{-4}	5
Milk Balance Tank (*n=3*)	1.16 x 10^{-4}	2
Centrifugal feed Pump (*n=4*)	3.37 x 10^{-4}	5
Pasteurizer Plant (*n=5,7,8,9,10*)	2.31 x 10^{-4}	8
Homogenizer (*n=6*)	4.62 x 10^{-4}	1
Culture Tank (*n=11, 12, 13*)	2.31 x 10^{-4}	4
Pouch Filling Machine (*n=14, 15*)	4.62 x 10^{-4}	3
Cup Filling Machine (*n=16, 17*)	2.31 x 10^{-4}	3

Using Eq. (2) for TMF, the collected λ_i and τ_i data were fuzzified and converted into triangular fuzzy numbers at different spread (± 15 %, ± 25 %, ± 60 %) in order to consider the vagueness/uncertainty in the raw data. Using Eqs. (3-6), mathematical modeling for the top event as per the developed PN model was generated. Fuzzified data were used in the developed mathematical modeling and reliability indices at different spread (± 15 %, ± 25 %, ± 60 %) for α -cut values varies between 0-1, were tabulated using reliability expressions (Table 2). Here, for illustration, reliability indices at left and right spread for 15 % are shown in Tables 4 and 5, respectively.

Table 4 Reliability indices left spread values at ± 15 %

DOM	Failure Rate	Repair Time	MTBF	Reliability	Availability
1	0.002294	0.006595588	436.00222	0.680230	0.999985
0.9	0.002259	0.006331246	429.54961	0.676304	0.999984
0.8	0.002225	0.006076471	423.28481	0.672400	0.999983
0.7	0.002190	0.005830808	417.19973	0.668519	0.999982
0.6	0.002156	0.005593833	411.28674	0.664660	0.999981
0.5	0.002121	0.005365154	405.53864	0.660823	0.999980
0.4	0.002087	0.005144404	399.94862	0.657008	0.999979
0.3	0.002052	0.004931242	394.51024	0.653214	0.999978
0.2	0.002018	0.004725348	389.21742	0.649443	0.999977
0.1	0.001984	0.004526426	384.06437	0.645693	0.999975
0	0.001949	0.004334196	379.04564	0.641964	0.999974

Table 5 Reliability indices right spread value at ± 15 %

DOM	Failure Rate	Repair Time	MTBF	Reliability	Availability
1	0.002294	0.006595588	436.00222	0.680230	0.999985
0.9	0.002328	0.006869987	442.65123	0.684178	0.999986
0.8	0.002363	0.007154971	449.50573	0.688149	0.999986
0.7	0.002397	0.007451111	456.57541	0.692143	0.999987
0.6	0.002431	0.007759025	463.87059	0.696160	0.999988
0.5	0.002466	0.008079379	471.40221	0.700200	0.999989
0.4	0.002500	0.008412898	479.18199	0.704263	0.999989
0.3	0.002535	0.008760368	487.22239	0.708349	0.999990
0.2	0.002569	0.009122641	495.53674	0.712459	0.999990
0.1	0.002604	0.009500648	504.13929	0.716593	0.999991
0	0.002638	0.0098954	513.04531	0.720750	0.999992

Similarly, fuzzified values are tabulated for ± 25 % and ± 60 %. Due to space limitations these values are not shown here. Here, on the basis of the operational engineer feedback, mission time (*t*) was considered as 168 hrs for tabulating various reliability indices. Using Eq. (7), the fuzzified reliability indices values are converted into crisp values as shown in Table 6 and are graphically shown in Fig. 4(a-g).

Table 6 Trends of reliability indices

Parameters	Crisp Value	Spread at ± 15 %	Spread at ± 25 %	Spread at ± 60 %	Trend
Failure rate	0.002294	0.00229367	0.00229380	0.00229475	Increasing Trend
Repair time	0.006595588	0.006942	0.007617	0.017243	
MTBF	436.0022241	442.697722	455.394389	599.625582	
ENOF	0.38531913	0.38533034	0.38535010	0.38548316	
Reliability	0.6802295	0.68098113	0.68231838	0.69230835	
Availability	0.99998487	0.9999834	0.99998064	0.99994043	Decreasing Trend
Unreliability	0.3197704	0.31901886	0.31768161	0.30769164	

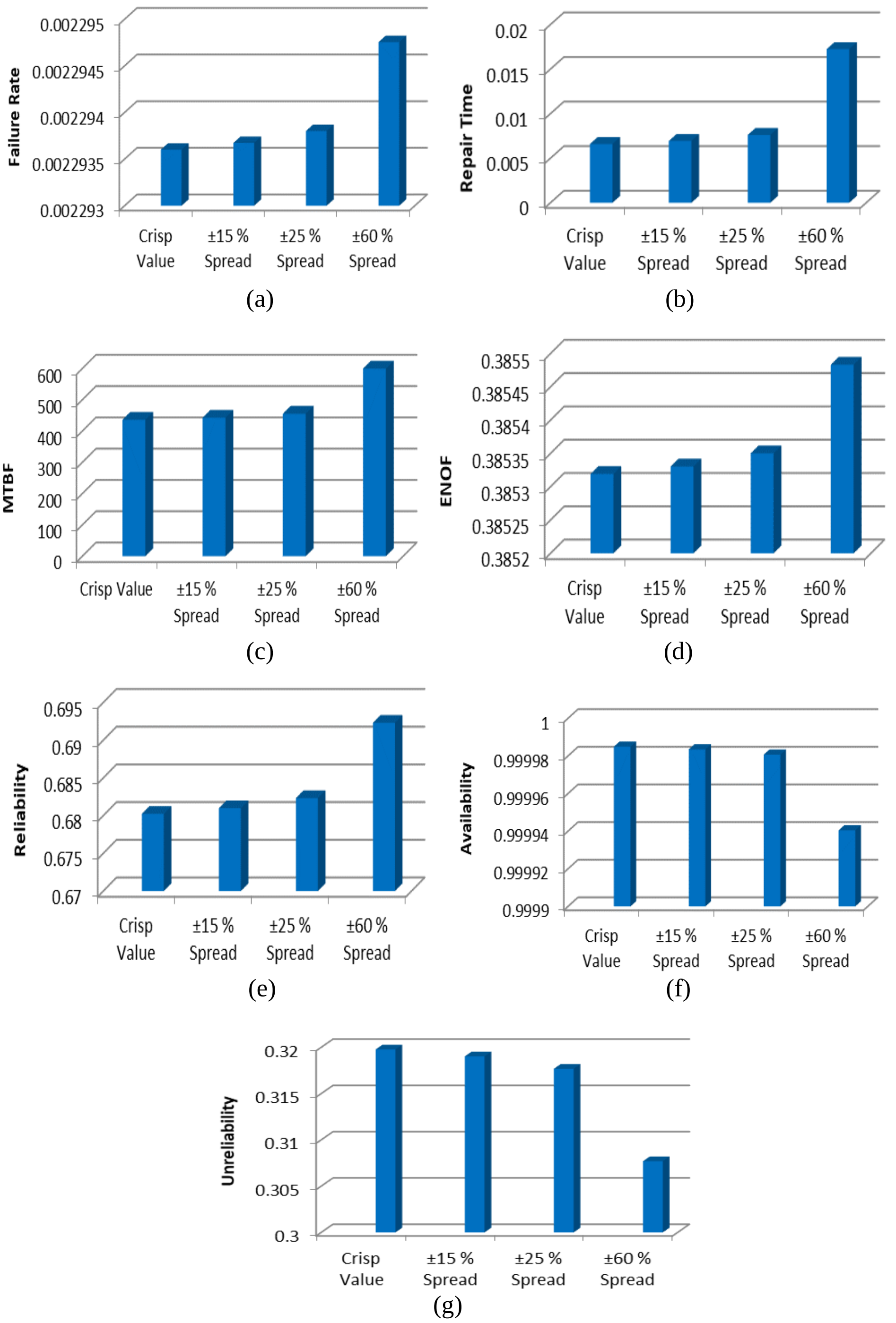

Fig. 4(a-g) Trends of reliability indices

4.1.2. Reliability analysis-based failure behavior

From Table 5, it is noted that the reliability indices, namely, repair time, failure rate, Mean Time Between Failure (MTBF), Expected Number of Failure (ENOF), Reliability and Unavailability are showing increasing trends with the increase in spread from ± 15 % to ± 25 % and ± 25 % to ± 60 %, respectively. On the other hand, availability shows a decrease in trend as the spread increases from ± 15 % to ± 25 % and ± 25 % to ± 60 %, respectively. Since the system availability shows a decreasing trend, in order to improve the availability and maintainability aspects, it is essential to carry a risk analysis of the considered unit as presented in Section 4.2.

4.2. Risk analysis

4.2.1. FMEA application

Failure Mode Effect Analysis (FMEA) sheet entails a failure mode; its effects and causes were prepared with the help of three maintenance experts' feedback. Here, due to space limitation, the FMEA detailed sheet with one expert's ratings feedback is shown in Table 10. Linguistic scales (Tables 7-9) were developed and provided to the experts in order to put their feedback against each listed failure causes under three risk factors: O_f, S and O_d.

Table 7 Linguistic variables for O_f

Linguistic variables	Probability of Failure	TFN
Very High (VH)	0-2 months	(8,9,10)
High (H)	2-5 months	(6,7,8)
Medium (M)	5-8 months	(4,5,6)
Fair (F)	8-10 months	(3,4,5)
Low (L)	10-12 months	(2,3,4)
Very Low (VL)	>1 year	(1,2,3)

Table 8 Linguistic variables for S

Linguistic variables	Severity effects	TFN
Very Serious (VS)	The level of severity is very high without warning	(8,9,10)
Very Extreme (VE)	The level of severity is high with warning	(7,8,9)
Major Damage (MD)	System is unavailable with component damage	(6,7,8)
Moderate (MO)	Performance of system is affected and maintenance is required	(4,6,7)
Low (L)	Minor effect on system performance and minor maintenance is required	(2,3,4)
No effect (N)	No effect on system performance	(1,2,3)

Table 9 Linguistic variables for O_d

Linguistic variables	Likelihood of detection of failure	TFN
Uncertain (U)	Detection by opening the sub-system/component & failure not detected visually & required to be replace	(7,8,10)
Very Remote (VR)	Detection by opening the sub-system/component & failure seen visually	(6,7,8)
Remote (R)	Detection with the help of automatic devices	(4,5,6)
Moderate (MO)	Detection by Display	(3,4,5)
Certain (C)	Visual detection of operator	(1,2,3)

Table 10 FMEA detailed sheet with one expert's ratings feedback

SL NO	Components	Failure mode	Failure effect	Failure cause	O_f	S	O_d
1	**Milk storage tank & Centrifugal feed Pump (MSCP)**						
	Milk valve	Leakage	Milk Loss	Mechanical seal failure **($MSCP_1$)**	H	L	VR
	CIP valve	Proper closing/opening failure	Cleaning stops	Low pressure of air **($MSCP_2$)**	H	VE	C
	Pump	Failure of impeller	Milk flow rate loss	Impeller blade breakage **($MSCP_3$)**	F	VE	VR
	Mechanical Seal	Leakage	Seal wear	Seals run dry, the friction will cause heat to accumulate **($MSCP_4$)**	H	MO	C
	Motor	Electrical failure	Supply Breakdown	Overheating / Moisture lead to winding failure **($MSCP_5$)**	L	MD	U
2	**Milk Balance tank, Duplex Filter & Pasteurizer (MBFP)**						
	Butterfly valve	Closing/opening failure	Supply Breakdown	Over tightened **($MBFP_1$)**	H	L	C
				Seal packing failure **($MBFP_2$)**	VH	L	C
	Stainless steel filter	Choke	Flow rate reduces	Visible sediment of Milk Jam in filter **($MBFP_3$)**	L	MO	C
	Heat exchanger plates	Mechanical failure	Efficiency loss	Crack in steel plate **($MBFP_4$)**	VL	VE	VR
				Corrosion **($MBFP_5$)**	L	VE	VR
	Gasket	Leakage	Operational loss	Erosion **($MBFP_6$)**	VH	MO	C
3	**Homogenizer (H)**						
	Piston	Mechanical failure	Supply Breakdown	Insufficient lubrication **(H_1)**	VL	VE	U
				Thermal fatigue **(H_2)**	L	VE	U
	Piston seal	Oil Leakage	Pressure loss	Excessive Wear **(H_3)**	VH	MO	VR
	Crankcase	Oil contamination	Operation loss	Improper quality of oil **(H_4)**	VL	MD	VR
	Ball spring	Mechanical failure	Oil flow breakdown	Spring breakage **(H_5)**	F	MD	MO
	Main drive Motor	Mechanical and electrical failure	Operation loss	Overheating **(H_6)**	L	MD	U
				Winding failure **(H_7)**	F	MD	U
	V-Belt	Belt slippage	Power transmission interrupted	Insufficient tension **(H_8)**	VL	MD	VR
	Hydraulic Pressure setting system	Leakage	Drop in pressure	Air and water contamination **(H_9)**	VL	MO	VR
				Low fluid level **(H_{10})**	L	MO	VR

SL NO	Components	Failure mode	Failure effect	Failure cause	O_f	S	O_d
4	**Culture Tank (CTK)**						
	Tank	Leakage	Loss of Milk	Improper insulation **(CTK_1)**	VL	MD	C
	Agitator Motor	Mechanical and Electrical failure	Supply Breakdown	Overheating **(CTK_2)**	F	MD	R
				Winding failure **(CTK_3)**	F	MD	R
	Agitator Blade	Mechanical failure	No proper mixing	Blade breakage **(CTK_4)**	VL	L	C
	Agitator Gear box	Mechanical failure	Breakdown	Improper lubrication **(CTK_5)**	L	VE	U
				Wearing in gears **(CTK_6)**	VL	VE	U
5	**Pouch filling machine (PFM)**						
	Element	Electric failure	Sealing interrupted	Too High temperature **(PFM_1)**	VH	MD	C
	Head Gasket	Leakage	Operational loss	Erosion **(PFM_2)**	H	MO	C
	Head Spring	Mechanical failure	Machine breakdown	Spring breakage **(PFM_3)**	VH	MD	VR
	Injection coil	Mechanical failure	Machine breakdown	Coil breakage **(PFM_4)**	L	MD	R
	Injection sheet	Mechanical failure	Milk continue to supply i.e. Milk loss	Bearing failure **(PFM_5)**	L	VE	VR
				Rubber failure which is below the sheet **(PFM_6)**	L	VE	VR
	Servo Motor	Electrical and Mechanical failure	Supply to pouch Breakdown	Overheating **(PFM_7)**	F	VE	R
				Too much moisture **(PFM_8)**	F	VE	R
	Grippers	Mechanical failure	Fail to hold pouch	Wear & Tear **(PFM_9)**	F	MD	C
	Gear box	Mechanical failure	Breakdown	Improper lubrication **(PFM_{10})**	M	MD	R
				Wearing in gears **(PFM_{11})**	L	MD	C
	Cam	Mechanical failure	Breakdown	Fatigue & Wear due to Corrosion **(PFM_{12})**	L	MD	U
	Belt	Belt slippage	Power transmission interrupted	Insufficient tension **(PFM_{13})**	M	MO	U

SL NO	Components	Failure mode	Failure effect	Failure cause	O_f	S	O_d
6	**Cup filling machine (CFM)**						
	Proximity Sensor	Diagnostic bit idle	Cup will not be detected	Sense gap between sensor face and trip face **(CFM_1)**	H	MO	C
	Vacuum Rubber	Mechanical failure	Cup will not be pulled out	Rubber breakage **(CFM_2)**	M	MD	VR
				Spring breakage **(CFM_3)**	M	MD	C
	Sealing Die	High temperature	Sealing interrupted	Element breakage **(CFM_4)**	VL	MD	C
	Injection Rod	Mechanical failure	Cup filling problem	Gasket seal breakage **(CFM_5)**	VL	MD	VR
	Cylinder air valve	Excessive heat	Air control will get interrupted	Due to heat **(CFM_6)**	F	MO	VR
	Air cylinder	Mechanical failure	Sealing die breakdown	Cylinder leakage **(CFM_7)**	L	MO	VR
	PLC controller	Input/output module failure	Machine breakdown	Voltage supply **(CFM_8)**	VL	MD	C

4.2.2. FCOPRAS Application

FCOPRAS approach was implemented within the traditional FMEA approach in order to overcome its limitations as discussed in Section 3.2.2. Under the FCOPRAS implementation, using fuzzy linguistic rating scales for three risk factors (Tables 6-8), the initial fuzzy decision matrix for the set of listed failure causes is generated using Eq. (8). Here, for illustration, the initial fuzzy decision matrix for the set of failure causes listed under first subsystem/component (MSCP) is generated as:

$$\tilde{m}_{ij} = \begin{bmatrix} (6,7,8),(4,5,6),(6,7,8) & (2,3,4),(6,7,8),(4,6,7) & (6,7,8),(4,5,6),(6,7,8) \\ (6,7,8),(8,9,10),(6,7,8) & (7,8,9),(7,8,9),(7,8,9) & (1,2,3),(4,5,6),(1,2,3) \\ (3,4,5),(4,5,6),(4,5,6) & (7,8,9),(6,7,8),(6,7,8) & (6,7,8),(1,2,3),(6,7,8) \\ (6,7,8),(3,4,5),(8,9,10) & (4,6,7),(4,6,7),(2,3,4) & (1,2,3),(1,2,3),(6,7,8) \\ (2,3,4),(1,2,3),(2,3,4) & (6,7,8),(6,7,8),(6,7,8) & (7,8,10),(4,5,6),(7,8,10) \end{bmatrix}$$

The initial fuzzy decision matrix for the set of failure causes listed under other subsystem/components was generated in the same way. For considering the effect of all three experts, their average was taken, and a modified initial fuzzy decision matrix for the set of listed failure causes was generated. Here, for illustration, the modified initial fuzzy decision matrix for the set of failure causes listed under first subsystem/component (MSCP) is represented as:

$$\tilde{m}_{ij} = \begin{bmatrix} (5.3333,6.3333,7.3333) & (4,5.3333,6.3333) & (5.3333,6.3333,7.3333) \\ (6.6667,7.6667,8.6667) & (7,8,9) & (2,3,4) \\ (3.6667,4.6667,5.6667) & (6.3333,7.3333,8.3333) & (4.3333,5.3333,6.3333) \\ (5.6667,6.6667,7.6667) & (3.3333,5,6) & (2.6667,3.6667,4.6667) \\ (1.6667,2.6667,3.6667) & (6,7,8) & (6,7,8.6667) \end{bmatrix}$$

The modified initial fuzzy decision matrix for other set of failure causes listed under FMEA sheet was generated in the same manner. Using the modified initial fuzzy decision matrix values in Eqs. (9-10), a crisp values-based decision matrix for set of listed failure causes was developed. Here, for illustration, the crisp values-based decision matrix for the set of failure causes listed under first subsystem/component (MSCP) is represented as:

$$m_{ij} = \begin{bmatrix} 6.3333 & 5.27775 & 6.3333 \\ 7.6667 & 8 & 3 \\ 4.6667 & 7.3333 & 5.3333 \\ 6.6667 & 4.8888 & 3.6667 \\ 2.6667 & 7 & 7.1111 \end{bmatrix}$$

The crisp values-based decision matrix for other set of failure causes was also generated in the same way. Furthermore, using the crisp values-based decision matrix values in Eqs. (11) and (12), a normalized decision matrix for set of listed failure causes was generated. Here, for illustration, the normalized decision matrix for the set of failure causes listed under first subsystem/component (MSCP) is represented as:

$$\overline{m}_{ij} = \begin{bmatrix} 0.2262 & 0.1652 & 0.2489 \\ 0.2738 & 0.2462 & 0.1179 \\ 0.1667 & 0.2256 & 0.2096 \\ 0.2381 & 0.1504 & 0.1441 \\ 0.0952 & 0.2154 & 0.2795 \end{bmatrix}$$

For other set of failure causes a normalized decision matrix was generated in the same way. Using the normalized decision matrix in Eqs. (13-14), a weighted normalized decision matrix was generated for each set of listed failure causes under FMEA sheet. Here, weights for three risk factors are tabulated by implementing the fuzzy extent analysis method [39, 40]. Wang's scale as shown in Table 11 was used for collecting feedback from the plant's maintenance manager in order to develop a comparison matrix for weight calculation.

Table 11 Wang's scale for comparison matrix

Uncertain Judgment	TFN Scale
Approximately Equal	(0.50, 1, 2)
Approximately *m* times[a] more important	(m - 1, m, m + 1)
Approximately *m* times less important	(1/(m + 1), 1/m, 1/(m - 1)
Between *n* and *o* times[b] more important	(n, (n + o)/2, o)
Between *n* and *o* times less important	1/o, 2/(n + o), 1/n

In Table 11: [a]*m= 2 to 9 and* [b]*n, o=1 to 9, n < o.*

Based on the feedback, a comparison matrix was developed; following the mathematical modeling of the fuzzy extent analysis method [39, 40] weights for three risk factors were tabulated as shown in Table 12.

Table 12 O_f, S and O_d weights

	O_f	S	O_d	**Weight**
O_f	(1 1 1)	(2 3 4)	(1 2 3)	**0.5405**
S	(0.25 0.3333 0.5)	(1 1 1)	(1 2 3)	**0.3074**
O_d	(0.3333 0.5 1)	(0.3333 1 1)	(1 1 1)	**0.1520**

Due to space limitations, weight calculation for the three risk factors is not shown here. Using the tabulated weights for three risk factors in Eqs. (13) and (14), the weighted normalized matrix for the set of failure causes listed under first subsystem/component (MSCP) is represented as an illustration:

$$\overline{m}_{ij} = \begin{bmatrix} 0.1223 & 0.0499 & 0.0378 \\ 0.1480 & 0.0757 & 0.0179 \\ 0.0901 & 0.0694 & 0.0319 \\ 0.1287 & 0.0462 & 0.0219 \\ 0.0515 & 0.0662 & 0.0425 \end{bmatrix}$$

The weighted normalized decision matrix for other set of failure causes was generated in the same way. Further, using Eqs. (15) and (16), the sum for beneficial (BC_{+i}) and non-beneficial (BC_{-i}) criteria-based risk factors values were tabulated for each listed failure causes. For illustration, beneficial (BC_{+i}) and non-beneficial (BC_{-i}) criteria-based risk factor values for the set of failure causes listed under first subsystem/component (MSCP) are represented in Table 13 as:

Table 13 Relative output significance and performance scores based ranking results

Subsystem's components	BC_{+i}	BC_{-i}	R_i	U_i	Rank
$MSCP_1$	0.0378	0.1722	0.1979	71.5325	3
$MSCP_2$	0.0179	0.2237	0.1411	51.0163	5
$MSCP_3$	0.0319	0.1594	0.2047	73.9922	2
$MSCP_4$	0.0219	0.1749	0.1795	64.8628	4
$MSCP_5$	0.0425	0.1177	0.2767	100	1

Beneficial (BC_{+i}) and non-beneficial (BC_{-i}) criteria-based risk factor values for other set of failure causes were tabulated in similar manner. Using beneficial (BC_{+i}) and non-beneficial (BC_{-i}) criteria-based risk factors values for each set of listed failure cause in Eqs. (17) and (18), relative output significance (R_i) and performance scores (U_i) were calculated and ranking was done in a descending order on the basis of U_i scores. Table 12 shows U_i based ranking results for the set of listed failure causes for first subsystem/component (MSCP) as illustration. Similarly, U_i score based ranking results were obtained for other set of failure causes listed under FMEA sheet and shown in ranking comparison Table 14.

Table 14 Ranking comparison for failure causes based on FCOPRAS and FTOPSIS outputs

Sr.No.	Failure Cause	COPRAS Output	COPRAS Rank	TOPSIS Output	TOPSIS Rank
1	$MSCP_1$	71.5325	3	0.3688	3
2	$MSCP_2$	51.0163	5	0	5
3	$MSCP_3$	73.9922	2	0.5643	2
4	$MSCP_4$	64.8628	4	0.3071	4
5	$MSCP_5$	100.0000	1	0.8336	1
6	$MBFP_1$	60.0240	4	0.5184	4
7	$MBFP_2$	49.9655	5	0.2438	5
8	$MBFP_3$	100.0000	1	0.9537	1
9	$MBFP_4$	74.5548	2	0.7941	2
10	$MBFP_5$	74.3876	3	0.7822	3
11	$MBFP_6$	42.0030	6	0.1775	6
12	H_1	87.7278	3	0.9064	3
13	H_2	82.0554	5	0.8880	4
14	H_3	43.3299	10	0.0751	10
15	H_4	100.0000	1	0.9820	1
16	H_5	51.0587	9	0.4093	9
17	H_6	74.4051	6	0.8413	6
18	H_7	70.1905	8	0.7952	7
19	H_8	73.7672	7	0.7623	8
20	H_9	88.3805	2	0.9256	2
21	H_{10}	82.7810	4	0.8747	5
22	CTK_1	70.7957	3	0.5910	3
23	CTK_2	52.6152	6	0.1381	6
24	CTK_3	55.0623	5	0.1862	5
25	CTK_4	100.0000	1	0.7179	1
26	CTK_5	65.1985	4	0.3792	4
27	CTK_6	79.9817	2	0.6534	2
28	PFM_1	44.0356	13	0.1098	13
29	PFM_2	48.4538	12	0.2198	11
30	PFM_3	53.2796	11	0.1689	12
31	PFM_4	91.4308	4	0.8810	3
32	PFM_5	96.0816	2	0.8900	2
33	PFM_6	77.8006	6	0.7362	7
34	PFM_7	73.7532	9	0.7241	8
35	PFM_8	77.4411	7	0.7382	6
36	PFM_9	67.0269	10	0.6561	10
37	PFM_{10}	76.6158	8	0.6998	9
38	PFM_{11}	100.0000	1	0.9094	1
39	PFM_{12}	92.3045	3	0.8770	4
40	PFM_{13}	78.4270	5	0.7396	5
41	CFM_1	46.4148	8	0.0250	8
42	CFM_2	69.3448	6	0.3808	6
43	CFM_3	65.2547	7	0.3577	7
44	CFM_4	99.3818	3	0.8158	3
45	CFM_5	99.6685	2	0.9187	2
46	CFM_6	74.4761	5	0.4957	5
47	CFM_7	100.0000	1	0.9207	1
48	CFM_8	80.2527	4	0.7602	4

4.2.3. FTOPSIS Application

For consistency check and effective decision-making of critical failure causes, the well known existing FTOPSIS approach was applied within the FCOPRAS approach. Using the weighted normalized matrix values as tabulated under the FCOPRAS approach, the ideal best solution (VV_j^+) and ideal worst solution (VVj^-) values for the three risk factors are computed. The ideal best solution (VV_j^+) and ideal worst solution (VVj^-) values for the set of failure causes listed under first subsystem/component (MSCP) are represented in Table 15 as an illustration.

Table 15 VV_j^+ and VVj^- for the three risk factors

Subsystem's components	O_f	S	O_d
$MSCP_1$	0.122257	0.049925	0.037848
$MSCP_2$	0.147997	0.075676	0.017928
$MSCP_3$	0.090085	0.06937	0.031872
$MSCP_4$	0.128693	0.046247	0.021912
$MSCP_5$	0.051478	0.066217	0.042496
VV_j^+	0.051478	0.046247	0.042496
VVj^-	0.147997	0.075676	0.017928

Similarly, VV_j^+ and VVj^- for other set of failure causes were tabulated. Further, using VV_j^+ and VVj^- values from each set of listed failure cause under different subsystem/component in Eqs. (19) and (20), the Euclidean distance from ideal best (SS_i^+), Euclidean distance from ideal worst (SS_i^-) were tabulated and the final performance score (FPS_i) was obtained by using Eq. (21). For illustration, the tabulated Euclidean distance from ideal best (SS_i^+), Euclidean distance from ideal worst (SS_i^-) and final performance score (FPS_i) with ranking for the set of listed failure causes under first subsystem/component (MSCP) are shown in Table 16.

Table 16 Ranking results based on final performance score

Subsystem's components	SS_i^+	SS_i^-	FPS_i	Rank
$MSCP_1$	0.0710	0.0415	0.3688	3
$MSCP_2$	0.1039	0.0000	0.0000	5
$MSCP_3$	0.0462	0.0599	0.5643	2
$MSCP_4$	0.0799	0.0354	0.3071	4
$MSCP_5$	0.0200	0.1000	0.8336	1

Similarly, for other set of listed failure causes, the Euclidean distance from ideal best (SS_i^+), Euclidean distance from ideal worst (SS_i^-) and final performance scores (FPS_i) were tabulated and ranking was done for the set of failure causes listed under FMEA sheet as shown in ranking comparison in Table 14.

4.2.4. Result discussion

From Table 14, it has been found that with the application of FCOPRAS & FTOPSIS approaches failure causes $MSCP_5$, $MBFP_3$, H_4, CTK_4, PFM_{11}, and CFM_7 associated with different subsystem/components of the considered curd unit with outputs 100,100, 100,100,100 and 100 & 0.8336,0.9537,0.9820, 0.7179, 0.9094 and 0.9207 are prioritized as most critical failure causes; responsible for decrease in system's availability. Furthermore, failure causes H_2, H_7, H_8, H_{10}, PFM_2, PFM_3, PFM_4, PFM_6, PFM_7, PFM_8, PFM_{10} and PFM_{12} shows little variation in the ranking results with the implementation of both FCOPRAS & FTOPSIS approaches. From Table 13, it is also noted that out of the total 48 listed failure causes, 36 listed failure causes show same ranking results, which indicates towards the consistency and effectivity of the proposed integrated framework.

5. Conclusion, Limitation and Future Scope of the Work

An integrated framework for studying the curd unit performance of a milk process industry has been proposed. TMF was used for the fuzzification of reliability and risk-based input data/information for achieving high accuracy in the performance-based results. Availability of the considered unit shows a decreasing trend with an increase in spread. Failure causes $MSCP_5$, $MBFP_3$, H_4, CTK_4, PFM_{11}, and CFM_7 associated with different subsystem/components of the considered unit are found to be most critical on the basis of their FCOPRAS and FTOPSIS output scores. FCOPRAS and FTOPSIS output scores based ranking results were compared for evaluating the consistency or robustness of the proposed integrated framework. The limitations of the traditional FMEA approach are covered effectively and an element of uncertainty in the accuracy of decision results was suppressed.

5.1. Managerial implications

The result outcome of this work was supplied to the maintenance manager of the considered milk process industry and was asked to implement these results for further testing. With the result outcomes the maintenance manager showed his keenness and expressed that once the top management made a decision to implement the results the usefulness of the proposed framework could be evaluated further.

From the proposed work, the following managerial implications are derived and communicated to the maintenance manager/reliability engineer of the curd unit of the considered milk process industry; he is able to make decisions related:

- To analyze and study the failure dynamics of the subsystem/components because of an increasing/ decreasing trend of reliability parameters.
- To consider the uncertainties/ vagueness associated with the raw data by incorporating a fuzzy based approach.
- To develop an optimum maintenance schedule for the considered unit in order to improve system's availability over long duration.

5.2. Limitations of the work

The analysis results so obtained with the implementation of the proposed framework will depend upon the quality of information/data provided by the maintenance experts. Therefore, the obtained results may be subjective in nature. However, by incorporating fuzzy set theory concepts in the proposed framework, the analyst can take care to eliminate the factor for biasness in the result outcomes.

5.3. Future scope of the work

In future, the proposed integrated framework could be presented with its application in order to study and analyze the performance issues of various other complex repairable systems of different process industries. The proposed framework could be modeled by incorporating other mathematical theories, namely, hesitant fuzzy and type-2 set fuzzy theories, etc. while the output results could be compared in order to evaluate the proposed framework effectivity in terms of its accuracy and robustness.

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