Sustainable Food Production

Subjects: Agricultural Engineering | Agriculture, Dairy & Animal Science | Computer Science, Artificial Intelligence
Contributor: Mehdi Khojastehpour

Fault diagnosis and prognosis methods are the most useful tools for risk and reliability analysis in food processing systems. Proactive diagnosis techniques such as failure mode and effect analysis (FMEA) are important for detecting all probable failures and facilitating the risk analysis process. However, significant uncertainties exist in the classical-FMEA when it comes to ranking the risk priority numbers (RPNs) of failure modes. Such uncertainties may have an impact on the food sector's operational safety and maintenance decisions.

Keywords: fault diagnosis ; support vector machine ; food industry ; maintenance ; sustainability ; uncertainty

1. Introduction

With the increasing automation and development of smart technologies in modern food industries, the higher guarantee of functional safety and reliability is poised to be the major challenge towards sustainable food production [1][2][3]. In this context, the intelligent platforms provide the hardware and software solutions for process control and safety management within many food manufacturing systems [4][5]. They attempt to represent the novel fault diagnostic and prognostic methods for risk predicting and analysis processes [6][7]. One of the most essential parts of risk in analyzing system reliability and safety is the risk analysis procedure [8][9][10]. In general, the novel methods are mainly classified into the knowledge-based and data-driven approaches for risk and reliability analysis and prediction under various situations [11][12][13].

In such circumstances, there are many types of knowledge-based approaches that refer to fault diagnosis and risk analysis, such as fault tree analysis (FTA), hazard analysis, critical control points (HACCP), root cause analysis (RCA), etc. [14][15][16]. Among them, the failure mode and effect analysis (FMEA) technique is widely used in numerous industries to assess and mitigate the risk of unexpected failures [17]. Besides, it has been a well-established procedure for upgrading the production quality and reducing the severity and occurrence of failure using corrective tasks [18]. A complete FMEA dominated by experts' knowledge includes the following four main steps: identifying the failure modes, determining their causes and effects, ranking the risk of failure modes, and finally suggesting the maintenance activities for the high-risk failures [19]. A risk priority number (RPN) is frequently inserted in a traditional FMEA to evaluate the risk level of a process, rank failures, and prioritize maintenance operations [20]. The RPN value is calculated by multiplying the following three risk parameters: occurrence (O), severity (S), and detection (D). They are ranked from 1 to 10 on a discrete ordinal scale. Ultimately, by arranging the RPNs in a descending order, the most critical failures can be identified [21].

The classical-FMEA has been particularly effective in detecting system bottlenecks and assessing the risk of failure modes in food production systems. They include the possibility of having the same RPN values, failing to assess the relative importance of risk parameters, and estimating the precise value of risk parameters incorrectly. Such major fluctuations in the real situation may not only affect the accuracy of estimated risks, but also the proposed maintenance and safety functions within food processing systems [21][22][23]. The main objective of this study is to take such uncertainties into account, particularly when ranking the RPNs of failure modes to supplement the current classical-FMEA in the food sector. The key contribution is a new systematic FMEA framework for risk analysis procedure based on certain well-known intelligent models to overcome RPN issue classification within an edible oil purification plant. The intelligent techniques include the fuzzy inference systems (FIS), adaptive neuro-fuzzy inference systems (ANFIS), and support vector machine (SVM) models. The findings of the current study could help managers to establish practical functional safety and maintenance programs in the edible oil industry.

The remainder of this research is organized as follows: A description of the literature linked to various types of FMEA in the food sector and its associated uncertainties in the risk analysis process is included in the part "Literature review." The "Research methodology" section compares the traditional and intelligent-FMEA risk analysis methodologies to come up with an upgraded fault diagnosis framework. The "Results and Discussion" section contains the key comparison data of traditional and intelligent-FMEA risk analysis approaches, as well as how to use the results to propose appropriate maintenance tasks. Finally, the “conclusion” section is provided, along with further remarks and perspectives.

2. History

Over the years, various types of FMEA, such as process-FMEA (PFMEA), design-FMEA (DFMEA), and total-FMEA (TFMEA) have been conducted within a wide range of applications in food processing industries. **Table 1** presents a summary review of the applied FMEAs in the food sector. The PFMEA is known as the main practical solution tool for analyzing various risks in food processing. For example, a PFMEA framework was performed to recognize the main critical points and analyze the risk by determining the RPN in the processing of potato chips. The results revealed that packaging, storage, potato receiving, frying, and distribution were the main critical points with the highest RPN, respectively [23]. In another study, a combined structure of PFMEA and ISO22000 was carried out on poultry slaughtering and manufacturing. In their work, the critical failure modes with high risks were identified by determining the RPN. [24]. Following this study, analyzing the risk of salmon processing has been conducted using PFMEA and its conjunction with the ISO 22000. The research findings could be beneficial for the manufacturers and their customers [25]. One of the FMEA applications is to control the quality and safety of food products. For example, the high quality of products has been a major challenge in the tea manufacturing industry. In this direction, a TFMEA model combined with the total quality management (TQM) technique was theoretically explored [26]. Following this, a FMEA structure for risk management in the confectionery industry has been designed to control system safety and quality [22]. In another work, a practical safety improvement plan for dairy product manufacturing under PFMEA analysis was suggested [27]. The results could be used by the manufacturers to produce safer dairy products. Another practical aspect of FMEA methods is its application to fault detection and optimization in food industries. For instance, the FMEA model was dedicated to allowing precise identification of food safety in verified HACCP systems. The incorporation of FMEA was verified to the procedure of the HACCP system in the bakery industry for better food safety assurance and fault detection [28]. Furthermore, a general structure of FMEA was suggested to detect the potential faults and their effects in primary food processing [29].

Table 1. A summary of literature review for FMEA applications in food industries.

Ref.	Year	Plant/ Process	Fault Diagnosis-Based Model		Sensitivity Analysis	Maintenance Activity
			FMEA Model	Computational/ Intelligent Model		
[23]	2007	Chips manufacturing plant	Classical PFMEA	-	-	-
[30]	2007	Corn curl manufacturing	Classical PFMEA	-	-	-
[25]	2008	Salmon processing and packing	Classical PFMEA	-	-	-
[24]	2009	Poultry product processing	Classical PFMEA	-	-	-
[26]	2011	Tea processing plant	Classical TFMEA	-	-	-
[22]	2012	Confectionery manufacturing	Classical PFMEA	-	-	-
[27]	2013	Dairy products manufacturing	Classical PFMEA	-	-	-
[28]	2014	Bakery critical equipment	Classical PFMEA	-	-	-
[29]	2016	General study	PFMEA	Fuzzy set theory	-	-
[31]	2017	Vegetable processing	PFMEA	Fuzzy set theory	-	-
[32]	2018	Meat production and processing	PFMEA	Fuzzy inference system	-	-
[33]	2019	General study	Classical PFMEA	-	-	-
Current study		Edible oil industry	PFMEA	Fuzzy inference system, ANFIS & SVM	✓	✓

A summary of the literature, the application of FMEAs in the food sector can be divided into several topics such as analyzing the risks, finding the critical points, improving the quality and safety, and selecting the maintenance activities. Despite the advantages of classical-FMEAs in the food industry, they have been criticized for several flaws and limitations that may affect proposed maintenance and safety decisions. The majority of epistemic uncertainties are included in the new systematic FMEA framework to improve the prior classical-FMEA in the food business. Intelligent approaches, on the other hand, have been deemed a very valuable alternative to enhance the accuracy of classical-FMEA for risk analysis under various uncertainties [34][35].

During the last few years, intelligent techniques such as support vector machine (SVM), fuzzy inference systems (FIS) and, adaptive neuro-fuzzy inference systems (ANFIS) have given great attention to modeling the FMEA and risk analysis processes. The FIS model, for example, has been used in the field of FMEA due to its software programming-based approach and its capacity to avoid cumbersome computations [19][36][37]. Currently, a comprehensive survey on the FIS-FMEA model was conducted with various rules and membership functions [MFs]. Based on the results, the combined MFs and model with a 10-class of fuzzy numbers have a higher possibility to create the larger risk cluster of failure modes [17]. Simşek and Ic [38] conducted an FMEA using a FIS model to evaluate and eliminate potential failure modes in a ready-mixed concrete plant. Their findings revealed that the fuzzy-rule-based system was effective in identifying and eliminating potential failure modes. Yucesan et al. [39] proposed a holistic FMEA approach based on a fuzzy-based Bayesian network and the best–worst method to deal with uncertain failure data. The proposed model might resolve the uncertainty in failure data and give a strong probabilistic risk analysis logic to represent the dependency between failure events in a manufacturing plant. The FUCOM and CoCoSo approaches were considered by Yousefi et al. [40] to improve the classical-FMEA technique in an unpredictable setting. Furthermore, Z-number theory was used to combine the ideas of reliability and uncertainty in evaluating the weight of risk variables. In an actual case study, the Z-FUCOM-CoCoSo approach was compared to the Fuzzy FMEA technique and a fuzzy variant of this approach. It was found that the Z-FUCOM-CoCoSo approach could provide the most feasible separation among failure modes when compared to traditional techniques. Rezaee et al. [41] presented a hybrid approach based on the Linguistic FMEA, FIS, and fuzzy data envelopment model to calculate a score for covering some RPN shortcomings and the prioritization of risks within the chemical industry. The results demonstrated that the proposed approach was very effective in prioritizing risks by taking uncertainty into account. In addition, to handle the uncertainties of classical-FMEA in other literature, the hybrid perception of fuzzy rule-based theories has been given a lot of attention [42][43][44].

On the other hand, the ANFIS model, with the benefits of both neural networks (NNs) and FIS principles in a single framework, has been used to reinforce the FMEA capabilities and manage the uncertainties in risk analysis [45][46][47]. For instance, an ANFIS model was developed to improve risk management and manage the uncertainties in risk variables. The proposed model was more convenient and efficient concerning risk management for single and clustered station facilities in transportation systems [48]. Moreover, the SVM algorithms constitute powerful regression and classification capabilities with that of FIS, neural networks (NNs), or genetic algorithms (GAs). They generally suffer from the presence of multiple local minima, structure selection problems, and overfitting issues [49][50][51]. Meanwhile, the SVMs have been approved as validation methods for failure mode analyses, fault detection as well as risk assessment in industrial fields [52][53][54][55].

Based on the literature, the performance comparison of such intelligent models in risk analysis, especially in food processing systems has not been previously evaluated. Hence, as the main motivation and innovation, we have contributed to proposing a new FMEA framework by intelligent techniques and comparing their outcomes with the classical model within food processing systems. In addition, given the need for monitoring the complex processes in the food sector, the proposed framework was implemented in the edible oil purification process. The outcomes were used to help the engineers to establish convenient safety and maintenance programs. Therefore, the main objective of this study is to propose a novel FMEA framework under intelligent techniques for analyzing the risks of the edible oil purification process.

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