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Enhancing risk assessment of manufacturing production process integrating failure modes and sequential fuzzy cognitive map

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ABSTRACT

When a risk occurs in a stage of the production process, it can be due to the risks of the previous stages, or it is effective in causing the risks in the later stages. The current paper proposes an intelligent approach based on cause-and-effect relationships to assess and prioritize a manufacturing unit's risks. Sequential multi-stage fuzzy cognitive maps (MSFCMs) are used for drawing the map of risks. Then, the learning algorithm is implemented for learning the MSFCM and finalizing the risks score. A case study on an auto-parts manufacturing unit is applied to demonstrate the capabilities of the proposed approach.

KEYWORDS

Auto-parts manufacturing; brake pads; multi-stage fuzzy cognitive maps; process failure modes and effects analysis; Risk assessment

1. Introduction

Due to the increasing trend of people's desire for personal transportation in daily life, and consequently, the increasing number of traffic accidents and their excessive risks, a part of the car called brake pads plays an important role in car safety and passengers' lives. Most people who are familiar with cars' mechanisms or experience in driving know that stopping a car is more crucial than starting and driving. A car that does not start will not pose any danger to the driver, passengers, or even the car itself. However, if the car's brakes do not work correctly, it could be a death trap. The brake is a mechanism to slow down or stop the car from moving. In these processes, the kinetic energy of the car is converted to heat by abrasive action. Therefore, brakes are the most important part of car safety, and if the brakes work correctly and prevent accidents, safety devices such as airbags are less commonly used. Thus, it is essential to pay attention to the car's safety and the passengers' lives. Therefore, all available tools must be used to produce safe and high-quality brake pads so that the lives of the passengers and other human beings are not endangered. To this end, the manufacturing process's failures leading to the production of defective products with low quality should be extracted to corrective actions to be carried out on them.

Failure mode and effects analysis (FMEA) is a valuable risk assessment technique, which has been introduced as a credible technique among risk assessment techniques (Rezaee et al. 2018). FMEA, as an analytical technique, defines, identifies, and eliminates known and/or potential failures, problems, errors of the system, design, process, and/or service before they reach the customer (Liu, Liu, and Liu 2013). The main purpose of FMEA is to identify potential failure modes, evaluate the causes and effects of different component failure modes, and determine what could remove or alleviate the chance of failure. Analysts can apply the analysis results to identify and correct the failure modes that have a detrimental effect on the system and improve its performance during design and production stages (Liu, Liu, and Liu 2013). The risk priority orders of the identified failure modes are determined by a risk priority number (RPN) score. The RPN is calculated by multiplying the three risk factors: occurrence (O), severity (S), and detection (D), where S and O denote the severity and occurrence of a failure, and D is defined as the probability of the failure not being detected before it reached the customer (Liu et al. 2019). Although traditional FMEA has been proven to be one of the most significant early preventative actions that will prevent failures and errors from occurring, the conventional RPN

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method has been criticized extensively in the literature for many reasons (Liu, Liu, and Liu 2013). Liu, Liu, and Liu (2013) summarized some of the most critical drawbacks of conventional RPNs as follows: the relative importance among S, O, and D is not considered, different combinations of S, O, and D may produce the same value of RPN, but their hidden risk implications may be completely different, the formula for calculating RPN does not have a strong mathematical background, the conversion of scores is different for the three risk factors, the RPN cannot be implemented to evaluate the effectiveness of corrective actions, etc. Furthermore, RPN independently determines SOD factors for each failure and disregards causal relationships between failures. Accordingly, it leads to the change in the priority of studied failures, which is one of its fundamental problems (Rezaee et al. 2018). In the real world and according to the process-oriented view, production stages are not implemented simultaneously. Moreover, potential failures do not occur simultaneously; some failures are affected by the failures of previous stages and/or subsequent stages (Rezaee et al. 2018).

Due to the problems mentioned above and the high importance of producing safe brake pads with high quality to work correctly in driving, an integrated approach is implemented in the present paper. The approach is based on the combination of process failure mode and effects analysis (PFMEA) and multi-stage fuzzy cognitive map (MSFCM). MSFCM was introduced by Rezaee, Salimi, et al. (2017) for considering the impact of previous and subsequent failures on the current failures in a stage-by-stage perspective. This method considers causal relationships between different failures of the previous and subsequent stages and is a more reliable and logical method to calculate RPN scores. In the first step of this approach, potential failures of the manufacturing process of the brake pads are determined in every stage of the production process based on the view of the cross-functional team (CFT). FMEA technique is one of the most practical methods for identifying, classifying, analyzing, and evaluating hazards and their risks in the industries. Parsana and Patel (2014) used FMEA to identify and eliminate current and potential problems from a manufacturing process of the cylinder heads company for improving the reliability of subsystems. Nguyen, Shu, and Hsu (2016) considered the quality cost and capacity as key factors for developing RPN scores, and the extended RPN score was assessed in a non-woven fabric manufacturing industry. Fattahi and Khalilzadeh (2018) applied the fuzzy weighted RPN for failures, and SOD factors' weight, then failure modes were computed by extended fuzzy analytic hierarchy process (AHP) as well as fuzzy multiple multi-objective optimizations by ratio analysis (MULTI-MOORA) methods in a steel manufacturing industry. Baynal, Sarı, and Akpınar (2018) proposed an integrated method combining gray relational analysis (GRA) with FMEA to contribute to risk management activities by proposing solutions to assembly-line problems in an automotive manufacturing company. Foroozesh, Tavakkoli-Moghaddam, and Mousavi (2018) proposed a new FMEA model based on multi-criteria decision-making (MCDM) by a group of supply chain-experts with interval-valued fuzzy settings and asymmetric uncertainty information concurrently in the manufacturing services. Li and Chen (2019) introduced a novel evidential FMEA integrating fuzzy belief structure and gray relational projection method to avoid using traditional RPN in a sheet steel production process of a steel manufacturing factory. Soltanali et al. (2019) proposed a comprehensive survey to overcome the drawbacks of the traditional FMEA through incorporating the fuzzy inference system (FIS) and effective attributes, including various scales and rules, different membership functions, various defuzzification algorithms, and their impacts on fuzzy RPN in an automotive production line. Boral et al. (2020) proposed a novel integrated MCDM approach by combining the fuzzy AHP with the modified fuzzy multi-attribute ideal real comparative analysis (modified FMAIRCA) to improve the risk estimation process in FMEA. Mangeli, Shahraki, and Saljooghi (2019) used a hybrid method according to the support vector machine and FIS to reduce the effect of personnel's opinions in determining the factors of the severity and occurrence. Moreover, logarithmic fuzzy preference programming was implemented to ascertain the crisp weight of the dependent factor of FMEA and revised the fuzzy technique for order of preference by similarity to ideal solution (TOPSIS) used for a more accurate ranking of risks. Onari, Yousefi, Rabieepour, et al. (2021) implemented the combination of Z-number and MSFCM to consider the uncertainty in the car manufacturing industry and trained the MSFCM with fuzzy numbers.

Afterward, each failure is considered as a concept of the MSFCM according to the manufacturing process. To calculate the initial value of the concepts, they are considered an objective node for fuzzy cognitive map (FCM), and SOD factors are taken into account as the concepts of FCM. By training FCM,

Table 1. Traditional FMEA scales.

Rating	Severity (S)	Occurrence (O)	Detection (D)
10	Hazardous without warning	Extremely high; failure is almost inevitable	Absolute uncertainty
9	Hazardous with warning	Very high	Very remote
8	Very high	Repeated failures	Remote
7	High	High	Very low
6	Moderate	Moderately high	Low
5	Low	Moderate	Moderate
4	Very low	Relatively low	Moderately high
3	Minor	Low	High
2	Very Minor	Remote	Very high
1	None	Nearly impossible	Almost certain

the initial value of concepts is obtained. FCMs are used for modeling complexity and management procedures. They can successfully demonstrate knowledge and human experience, introducing concepts and cause and effect relationships (Papageorgiou et al. 2017; Rezaee, Yousefi, and Hayati 2019). FCM possesses various applications in fields such as the decision support system (Douali et al. 2015), environmental science (Demertzis et al. 2018), supplier selection problem (Onari and Rezaee 2020), time series prediction (Lu et al. 2014), medical diagnosis (Papageorgiou et al. 2015), predicting the severity level of Covid-19 (Onari, Yousefi, Rabieepour, et al. 2021), etc. Furthermore, FCM can be implemented in risk assessment problems in various domains. Jamshidi et al. (2018) proposed an integrated generalized decision support tool for dynamic risk assessment of complex systems by employing FCM. Azar and Dolatabad (2019) proposed an integrated approach based on FCM and Bayesian belief networks (BBN) to ameliorate BBN's capability to model operational risks in an Iranian private bank. Dabbagh and Yousefi (2019) proposed a hybrid decision-making approach based on FMEA, FCM, and MOORA for assessing and prioritizing occupational health and safety risks. Chen, Zhang, and Wu (2020) proposed a robust model for integrating the structural equation model and FCM to perceive and assess the performance risk in public-private partnership projects. Afterward, the whole of the map is trained stage-by-stage according to the MSFCM method. Finally, after reaching the steady-state of the map, the failures are ranked based on their achieved scores.

The rest of the present article is organized as follows: In "Methodology", the implemented methods are introduced. In "MSFCM-PFMEA approach", the proposed approach to apply in the present study is described in detail. In "Case study", the studied case is presented. In "Analysis of the results", the results of the study are presented and analyzed. Finally, in "Conclusion", the conclusion is provided, and suggestions for future works are proposed.

2. Methodology

In this section, the proposed methods are presented, which are implemented in the current study. In the first sub-section, the concept of the PFMEA technique is introduced. In the second sub-section, the concept of FCM and MSFCM is presented. Then, in the third sub-section, the learning algorithm for the FCM and MSFCM is described.

2.1. PFMEA

The United States Defense Department, for the first time in 1949, introduced the FMEA, and the national aeronautics and space administration (NASA) applied that for the Apollo plan to enhance system reliability in the 1960s. Because of its visibility and simplicity, the method has been successfully implemented in various industries (Huang et al. 2020). FMEA method is one of the most practical methods for identifying, classifying, analyzing, and evaluating hazards and their risks. Organizations can identify risks and prevent them from occurring by implementing this method. FMEA is a systematic tool based on teamwork to recognize failures, causes, and effects of potential failures, control, and preventive actions in a system before production or service is delivered to the customers (Rezaee, Salimi, et al. 2017). PFMEA consists of possible effects and mechanisms of failure modes which are defined by the team. PFMEA is a living and dynamic document that contains the changes in the product design process. PFMEA attempt to reduce the risks of failures in the process with the following steps (Baghery, Yousefi, and Rezaee 2018):

1. Identifying the potential failure modes related to the production process.

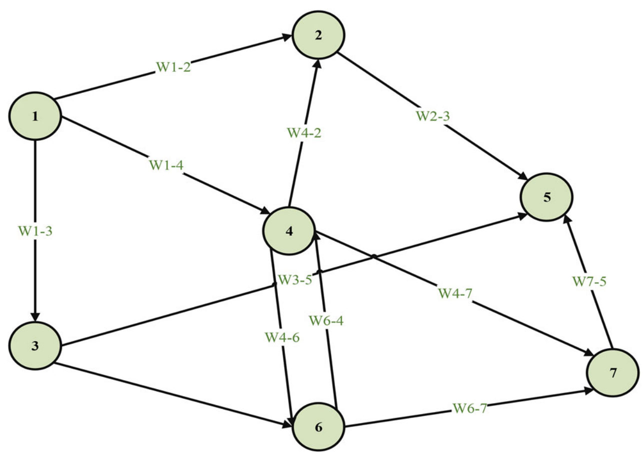

Figure 1. An FCM with seven nodes and 11 edges.

2. Confirming the severity of failure effects on the customer.
3. Identifying two main information: a) the potential causes in the manufacturing and assembly process; b) the process alteration when the controls concentrate on reducing the occurrence of failure or tracking the failure conditions.
4. Providing an arranged list of potential failure modes; thus, a prioritized system is established for taking corrective actions based on RPNs.
5. Documenting the manufacturing or assembly process results

The conventional RPN index is calculated by multiplying three factors of S, O, and D. These factors are illustrated in Table 1 and are ranked from 1 to 10. Hence, the score of 10 for risks in terms of severity means extremely dangerous (hazardous without warning). Also, the score of 10 in terms of occurrence means a certain occurrence (failure is almost inevitable), and in terms of detection means undetectable risk (absolute uncertainty) (Rezaee and Yousefi 2018).

2.2. FCM vs MSFCM concept

FCMs are fuzzy-graph structures for demonstrating causal relationships. Their fuzziness allows vague degrees of causality between vague causal objects (concepts). Their graph structure allows knowledge bases to be grown by connecting different FCMs (Kosko 1986). FCMs, as a structured AI technique that incorporates ideas from artificial neural networks (ANNs) and fuzzy logic, can create models as a set of causal relationships and concepts (Onari and Rezaee 2020). FCM was initially introduced by Kosko (1986) and has emerged as a tool for modeling and studying the behavior of complex systems (Salmeron and Lopez 2012). In the FCM, nodes represent the concepts, and edges denote the causal relationship between the concepts. The concepts indicate the key factors of the system (characteristics, and qualities, etc.) and are defined by $C_i, i = 1, \ldots, N$ where N is the total number of concepts. Each concept acquires an activation value $A_i \in [0,1], i = 1, \ldots, N$ and signed fuzzy weights W_{ij} of the edges between C_i and C_j where $j = 1, \ldots, N$ takes the values in the range $[-1,1]$ (Papageorgiou et al. 2015). $W_{ij} > 0$ represents a positive and $W_{ij} < 0$ represents a negative causal relationship. $W_{ij} = 0$ represents a lack of any relationship between the two concepts. For analyzing the model, it must be modeled by mathematical formulas after depicting the map. By calculating the node's values, the values of other nodes connected with this node can be obtained using Equation (1):

$$A_i^{(k+1)} = f\left(A_i^{(k)} + \sum_{\substack{i=1 \\ j \neq i}}^{n} W_{ij}^{(k)} A_j^{(k)}\right) \quad (1)$$

$A_i^{(k+1)}$ indicates the value of C_i in the iteration k + 1, $A_i^{(k)}$ indicates the value of C_i in the iteration k, and $f_{(x)}$ represents the normalization function, which usually is the sigmoid function (Rezaee and Yousefi 2018). An overview of an FCM is illustrated in Figure 1.

Rezaee, Salimi, et al. (2017) initially presented the concept of MSFCM to consider the process approach to model complex systems that technically include the various subsystems. The MSFCM consists of several conventional FCMs that are related to each other as the stage. These conventional FCMs are types of subsystems that nodes (concepts, components) have causal relationships with each other as well as other nodes of the existing subsystems simultaneously (Rezaee, Salimi, et al. 2017). In the MSFCM, causal relationships between nodes in stages are internal or external. Internal-stage causal relationships are the edges that connect considered FCM nodes in each stage. External-stage causal relationships are the edges that connect nodes from one stage to nodes from other stages (Rezaee et al. 2018). For instance, in Figure 2, $W_{A-1,A-2}$ is an internal relationship in stage A, and $W_{A-3,B-2}$ is an external relationship between stage A and B.

2.3. Learning algorithm based on the extended delta rule

In the FCM, precise estimation of map weights to increase their accuracy, improving the map's structure, and reducing dependency on experts' opinions by learning algorithms are important issues. The Hebbian

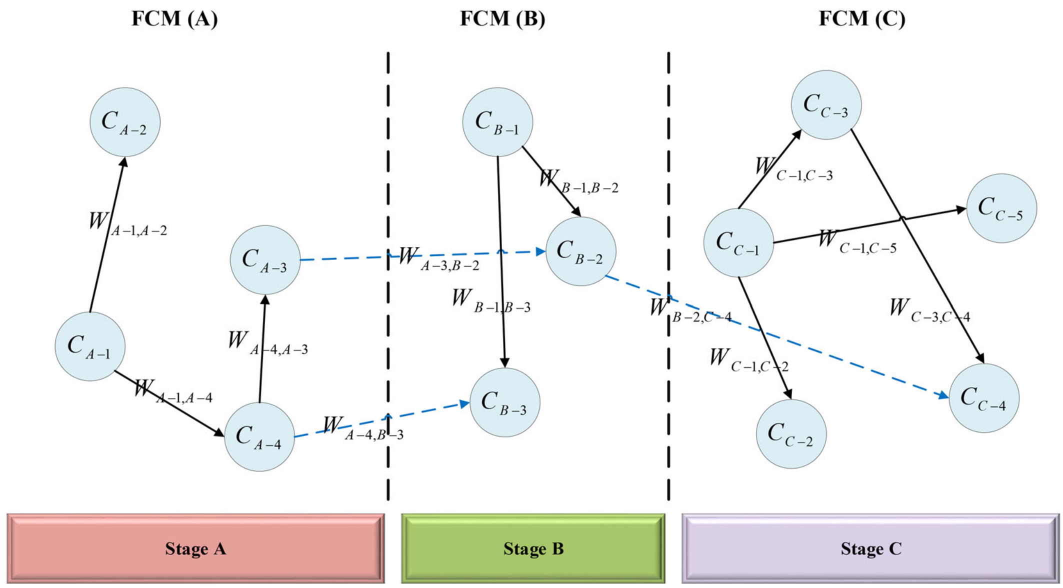

Figure 2. An MSFCM with three stages.

algorithm is one of the most popular FCM learning algorithms. It possesses different types such as differential Hebbian learning (DHL), active Hebbian learning (AHL), nonlinear Hebbian learning (NHL), and data-driven NHL. One of the shortcomings of Hebbian algorithms is the lack of convergence in some situations (Rezaee, Salimi, et al. 2017). For this purpose, Rezaee, Salimi, et al. (2017) introduced the Extended Delta rule algorithm concept. Figure 3 represents the implementation steps of the Extended Delta rule learning algorithm. In the first step, inputs contained a matrix of initial concept values, which is represented by a $1 \times N$ matrix as $A^{(0)}$ and an initial weights matrix, which is shown by $N \times N$ matrix $W^{(0)}$ and represents the weights between the system's concepts. After determining the input values, the matrix of initial concept values is determined based on each scenario (for every single stage). Subsequently, this algorithm is implemented and repeated for each iteration (k) until minimizing the sum of squared errors in Equation (2), where E is a function of all weights (edges in FCM) that its gradient is a vector consisting of partial derivatives E to any of the weights. Where $A_j(k)$ is the jth concept at iteration k, and t_j is the target value for the jth concept. In Step 3, the values of concepts are updated. By applying the transfer function (f), the concepts are calculated by Equation (1), the key formula of FCM.

$$E = \sum_{j=1}^{m} (t_j - A_j^{(k)})^2 \tag{2}$$

Then, weights are updated using Equation (3) and normalized in Steps 4 and 5, respectively (Papageorgiou et al. 2015, Rezaee, Salimi, et al. 2017).

$$w_{ij}^{(k+1)} = \gamma w_{ij}^{(k)} + \alpha (t_j - A_j^{(k)})^2 A_i^{(k)} \left(\frac{\partial A_j}{\partial w_{ij}} \right)^{(k)} \tag{3}$$

In Equation (3), $w_{ij}^{(k+1)}$ is referred to as the weight between C_i and C_j in iteration $(k+1)$ and $\left(\frac{\partial A_j}{\partial w_{ij}}\right)^{(k)}$ represents the derivative of A_j concerning w_{ij} in iteration (k). Besides, γ indicates the learning parameters. The value of t_j is required to use the learning algorithm because the Delta rule is a supervised learning algorithm that is based on the existence of target values for training vectors. In the current study, the values of normalized RPN can be used as t_j. In Step 4, the learning algorithm based on the Delta rule is employed to update causal relationships' weights. In Step 6, the termination condition is applied to this learning algorithm by using Equation (4), where $\frac{\partial E}{\partial w_{ij}}$ represents the derivative of E concerning w_{ij} and ε is a type of numbers which is not zero but near zero, and in the current study was set to be 0.00001 (Rezaee et al. 2018).

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial}{\partial w_{ij}} \sum_{j=1}^{m} (t_j - A_j^{(k)})^2 < \varepsilon \tag{4}$$

3. MSFCM-PFMEA approach

In this section, the implementation of the MSFCM method and PFMEA technique is presented to prioritize production process failures. In contrast to the previous studies, RPN has not been used to prioritize the failures in this research. Because all the methods

Extended Delta Rule:

Step 1: Read the input concept state A^0 and initial weight matrix W^0.

Step 2: Repeat for each iteration k until $E = \sum_{j=1}^{m}(t_j - A_j^{(k)})^2$ is minimized.

Step 3: Calculate $A^{(k)}$ based on $A_i^{(k+1)} = f\left(A_i^{(k)} + \sum_{\substack{i=1 \\ j \neq i}}^{n} W_{ij}^{(k)} A_j^{(k)}\right)$

Step 4: Update the weights based on $W_{ij}^{(k+1)} = \gamma w_{ij}^{(k)} + \alpha (t_j - A_j^{(k)})^2 A_i^{(k)} \left(\frac{\partial A_j}{\partial w_{ij}}\right)^{(k)}$

Step 5: Normalize $W^{(k+1)}$ (It is optional but recommended).

Step 6: Calculate $\frac{\partial E}{\partial w_{ij}} = \frac{\partial}{\partial w_{ij}} \sum_{j=1}^{m} (t_j - A_j^{(k)})^2 < \varepsilon$ (Termination function, $\varepsilon > 0$ is a very small value).

Step 7: Until the termination condition is met.

Step 8: Return the final weights ($W^{(k+1)}$) to Meta-heuristic algorithms if it is necessary.

Figure 3. Learning the FCM algorithm based on the Extended Delta rule (Rezaee, Salimi, et al. 2017).

related to RPN concentrate improvement efforts on a mode of failure, having higher RPN might have less impairment than the other failures with lower RPN. The other fundamental problem of the RPN index is that it does not consider the interrelations of failures that can lead to changing the priority of failures to address; the reason is that, in reality, some failures affect other failures or are affected by them. Thus, the suggested approach calculates the score of failure prioritization based on three criteria: severity, occurrence probability, detection probability, and cause-and-effect relationships between failures by using MSFCM instead of the RPN index, which does not include a cause-and-effect relationship. In the suggested approach, each stage is an index of production; to be more accurate, each stage shows the place of failure occurrence in a system. In other words, in any industry, failures occurring in each stage have resulted from that stage and the previous ones; in the suggested approach, the relationships of failures in each part with other parts have been considered. This approach considers the severity, occurrence, and detection factors of each failure. Furthermore, the existing relationships between failures are divided into internal-stage and external-stage relationships in this approach.

In the first step of the proposed approach, the PFMEA technique is applied to the case by the CFT. This step's output identifies failures in the production process and the values of SOD factors for each failure. Afterward, the RPN score can be calculated for each failure using the values of these factors. In the next step of the approach, all identified failures in the various stages of the manufacturing process are considered MSFCM concepts. These failures are connected by edges that indicate the causal relationships between failures. Moreover, each factor is considered a particular concept for each failure to apply the PFMEA triple factors. For instance, the first failure in an MSFCM and the probable relationship with other failures will have relationships with a deterministic weight of 1 with three factors of severity, occurrence, and detection. This action transmits the full impact of three factors' values to the concept of failure and only is implemented on the specific failure. The internal-stage and external-stage causal relationships between failures of the production process are weighed based on experts' opinions of CFT, and ultimately the weighting matrix of causal relationships is obtained. Now, the MSFCM can be depicted. Figure 4 demonstrates one of the stages of MSFCM.

As shown in Figure 4, Stage B of the MSFCM has been presented. Each concept (failure) has causal relationships with SOD factors allocated by the CFT, and they are input concepts of failures. Moreover, similar to conventional FCM, each concept has causal relationships with others. For instance, C_{B-1} is a failure, and SOD factors (S_{B-1}, O_{B-1}, D_{B-1}) are connected to that with the weight value of 1. Also, C_{B-1} and C_{B-2} are failures that have causal relationships with each other and also other failures in the other stages. Then,

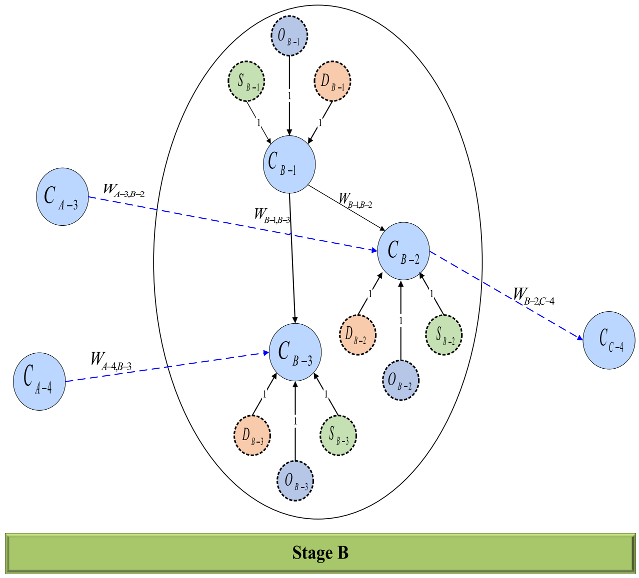

Figure 4. An overview of a stage of the MSFCM-PFMEA approach.

the score of prioritizations for each failure is calculated by defining each stage's scenario and applying the learning algorithm based on the extended Delta rule. Definition of the scenario for a stage consists of three assumptions: 1) it is assumed that all concepts implicating the failures in this stage have a normalized value; 2) SOD factors for each failure of this stage are considered in the scenario; 3) trained values of failures in the prior stage that has external-relationships with the studied stage are considered in the scenario.

After completing FCM calculations and achieving a steady state in the system, the score is obtained for each failure in each stage, which is the basis for prioritizing failures. This process will continue until the completion of the investigation process of all stages. This approach's output is the scores for all failures of the production process, in which the prioritization process is based on these scores. After investigating each stage, only nodes representing failures and having external relationships with the next stages remain, and other nodes with all internal relationships are excluded from the next calculation. After calculating the score for each system failure, it should be explained that prioritizing failures is possible. The failures' ranking is based on the high value of the obtained scores, and failures with high value will have a higher rank (Rezaee et al. 2018).

4. Case study

In the current study, the manufacturing process of brake pads of Shabnam Lent Co. has been investigated to prioritize manufacturing failures in the production process. As listed in Table 2, the production process of brake pads in this company includes many steps briefly mentioned in the following. Firstly, raw material weighing for one working day is carried out considering various ingredients (phenolic resins, steel wool, barite, slaked lime, aluminum oxide, black soot, ceramic fiber, etc.). Then, the mixing process initiates, and ingredients are mixed to form compounds. The process is accomplished using a single axle rotary mixer to ensure the highest mix level. The compound is then weighed and pressed in the form of standard blocks. The blocks are then cut to standard sizes by a pre-calibrated table. The prepared blocks are formed to the desired shape at the next step, which is extremely close to the final shape. Afterward, pieces are located inside the oven and cured thoroughly. Afterward, the side parts of the brake pads are removed by the grinding process. At the end of the manufacturing process, the block compounds are attached to the backing plate. Finally, quality control and storage are performed, respectively.

5. Analysis of the results

In this section, the proposed approach results based on the MSFCM and the Extended Delta rule are analyzed. After determining the risks of PFMEA by CFT and prioritizing them with RPN scores, their normal values are implemented to establish the MSFCM. After depicting the MSFCM and determining the causal relationships between failures, relationships' weights are assigned by the CFT (See Figure 5 and Appendix).

Then, the MSFCM is executed, and the final values for failures are obtained. The generated results are compared with the conventional FCM with the extended delta rule algorithm and the RPN score to validate the proposed approach.

In the first step of evaluating the proposed approach, the MSFCM is executed by the Delta rule learning algorithm. In this section, both internal and external relationships between failures are considered, and the map is trained stage-by-stage. After training the map, the results are presented in the first column of Table 3. The results show that the failures are ranked, and the most and least important failures are determined. The failures F4,1, F2,1, and F3,1 have the highest scores and are determined as the most critical failures. Also, particular actions should be considered to prevent devastating consequences. On the other hand, failures F7,3, F9,3, and F1,1 have the least score

Table 2. The list of failures of the manufacturing process and their SOD factors.

Step	Process	Failures		Severity	Occurrence	Detection
1	Raw material weighing	Human error	F1,1	8	4	2
		Measurement errors in measurement scales	F1,2	6	4	3
		Visual error	F1,3	4	3	4
		Material moisture/wetness problems	F1,4	2	4	2
		Impurity incorporation	F1,5	7	2	7
2	Materials mixing	Incomplete mixing of components	F2,1	3	2	2
		Impurity incorporation	F2,2	5	3	7
		Improper moisture content	F2,3	2	2	6
		Incorrect order in materials mixing	F2,4	7	2	1
3	Forming compounds into standard blocks	Heterogeneous hammering	F3,1	8	2	3
		Deficient hammering process from standard	F3,2	7	3	3
		Mold surface uncleanness	F3,3	5	4	2
4	Cut and resize compounds to blocks	Excessive curvature at the cutting edge	F4,1	7	5	2
		The cutting surface is not smooth	F4,2	5	3	2
		Inaccuracy in pallet removal (impact load)	F4,3	3	4	1
5	Blocks shaping according to the standard	Improper placement of the block piece in the form of die	F5,1	10	2	2
		Too much pressing pressure	F5,2	10	2	2
6	Condensate ingredients and curing blocks	Insufficient or excessive oven temperature	F6,1	10	4	4
		Temperature nonuniformity inside the oven	F6,2	6	2	5
		Non-uniform cooling in different parts of blocks	F6,3	6	2	5
		Improper curing time	F6,4	10	2	4
7	Grinding	Dimensional inaccuracy in the grinding process	F7,1	8	5	3
		High feed grinding	F7,2	5	5	3
		Grinding wheel runout	F7,3	6	4	2
8	Attach the brake blocks to the backing plate	Lack of adhesive quality	F8,1	8	2	3
		Scratch on the surface of the backing plate	F8,2	6	3	3
		Uncleanness of contacting surfaces	F8,3	6	3	3
		Adhesive impurities	F8,4	7	3	7
		Air trap in contacting surfaces	F8,5	9	3	6
9	Quality control and storage	Long-term storage	F9,1	6	2	1
		Lack of expiration date for the operation at different times, temperatures, and humidity	F9,2	7	5	1
		Inadequate storage	F9,3	5	2	1

and are considered failures with the least risk for the process.

In the next step, to validate the results based on the MSFCM and the Extended Delta rule, they are compared with the conventional RPN scores assigned by the CFT. As is obvious in the RPN column of Table 3, failures F8,5, F6,1, and F8,4 are considered the most critical failures. There are conspicuous differences between the generated results between the other two methods. It is due to the lack of the RPN index in considering the causal relationships between the failures in the various stages. Causal relationships exist between failures in different stages, and a failure in previous stages may affect other failures in the next stages. It is essential to recognize and relieve the crucial failures in the early stages. Consequently, determining the causal relationships between failures can directly relate to other failures in the next stages. It can be concluded that the conventional RPN index is not a reliable technique to determine the criticality of the failures. Furthermore, this behavior is observed in the least critical failures. In the RPN index failures, F2,1, F4,3, F9,1, and F9,3 have lower priority than other failures with notable differences with MSFCM.

In the last step, the MSFCM is compared with conventional FCM, which both of them implement the Extended Delta-rule as the learning algorithm. In the conventional FCM, there are no separate internal and external relationships between the process stages, and all failures are considered the whole. The purpose is to compare the impact of the multi-stage approach on the study with conventional FCM.

After defining scenarios for assessing existent failures in each system stage, the learning algorithm is implemented. The implementation of this algorithm requires two main inputs. The matrix of initial

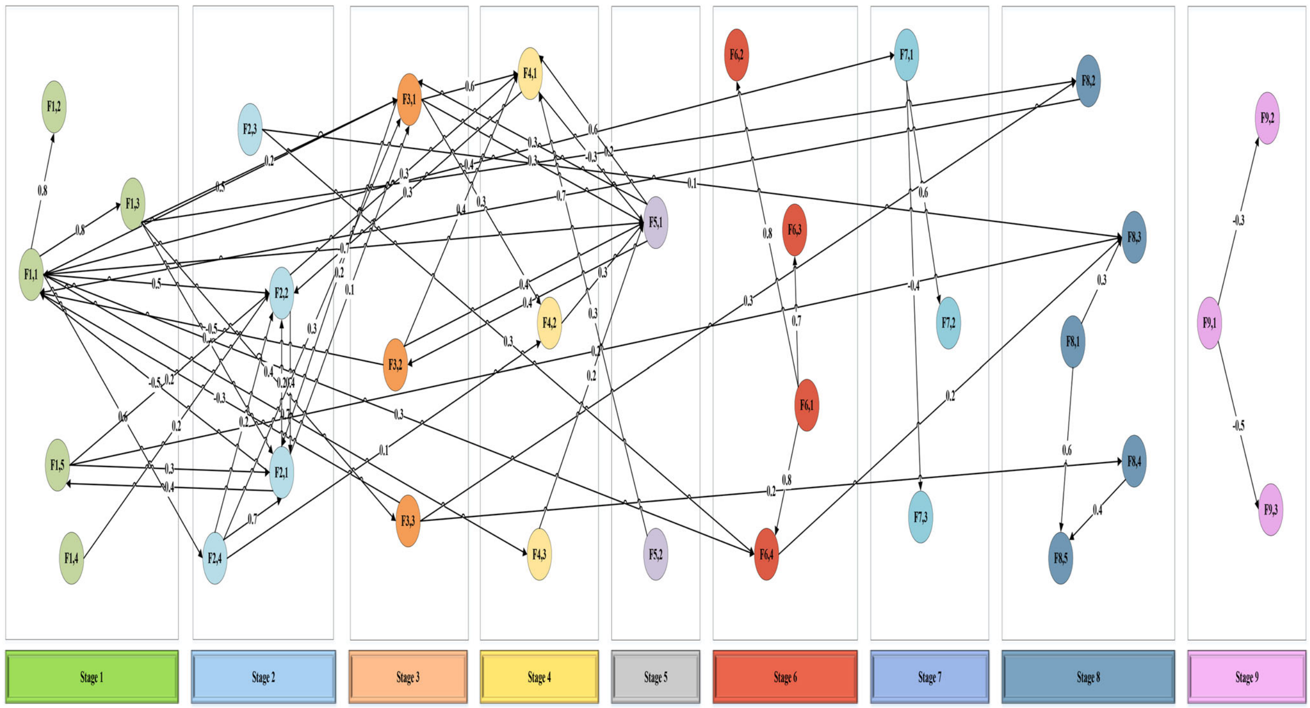

Figure 5. MSFCM for the studied case study.

concept values (failures and their SOD values) and the matrix of initial weights of causal relationships among concepts (see Appendix) are the main inputs of this algorithm. In the matrix of initial weights of causal relationships among concepts, the weights of causal relationships among failures are determined based on experts' opinions (CFT), and the weights of relationships among SOD factors and relevant failure are considered equal to 1, and the weights of relationships among SOD factors are considered equal to zero. But, an initial concept matrix of values is defined based on each scenario (for each stage); as in this matrix:

- The concepts related to the failures that existed in the stage under study have the value of 1 (are activated).
- The concept of previous stage failures associated with the external-stage causal relationships to the failures of the stage under study have the trained value of those failures (according to the implementation of the learning algorithm for the previous stages).
- The values of concepts related to SOD factors for existent failures in the stage understudy are the same as the normalized SOD values (the reason for using normalized values of the SOD factors is that the values of FCM concepts must be between zero and one).
- The values of other concepts are also considered equal to zero.

Finally, after an iteration of the learning algorithm, to prevent the excessive impact of the SOD factors, in the second iteration to next, the weight of causal relationships among these factors and the failure under study is considered equal to zero. Then, using the new matrices of trained values of the concepts and causal relationships weights, the implementation of the learning algorithm continues to reach the termination conditions, such as the required iteration.

After implementing the approach, failures F4,1 and F2,1 have the highest ranking between the failures and have nearly identical performance according to MSFCM. However, in this approach, the failure of F2,2 has the third-highest rank between failures, which has different results compared with MSFCM. It is due to the conventional perspective, which has been implemented on the FCM. There are no differences between the least important failures among the two algorithms. There are other differences between some failures' rankings, which exhibits significant differences between these two approaches. Meanwhile, based on the experts' opinion, the MSFCM has the closest results to the real-world results, and based on experts' experiences, the MSFCM performance was the best compared to the other two methods.

Finally, a comparison has been drawn between the prioritization results of the proposed approach and traditional FMEA priority score and popular MCDM methods such as TOPSIS and MOORA (Valipour et al. 2021). The results have been shown in Table 3.

Table 3. The generated results based on the proposed approach vs. other ranking methods.

	Multi-stage Delta-rule	Ranking	RPN	Ranking	Delta-rule	Ranking	MOORA score	Ranking	TOPSIS score	Ranking
F1,1	0.1674	32	64	11	0.1186	32	0.1753	10	0.4494	13
F1,2	0.7053	21	72	9	0.6920	18	0.1733	11	0.4483	14
F1,3	0.7053	21	48	17	0.6920	18	0.1534	23	0.3997	21
F1,4	0.6591	25	16	27	0.6591	23	0.1217	27	0.2740	27
F1,5	0.7416	19	98	6	0.7715	12	0.2099	5	0.6253	5
F2,1	0.9539	2	12	29	0.9408	2	0.0946	32	0.1356	32
F2,2	0.9266	4	105	5	0.8867	3	0.2101	4	0.6302	4
F2,3	0.6591	25	24	26	0.6591	23	0.1493	24	0.4588	12
F2,4	0.7922	13	14	28	0.6837	21	0.1144	29	0.2840	26
F3,1	0.9418	3	48	17	0.8507	5	0.1552	22	0.4192	19
F3,2	0.7847	15	63	12	0.7598	14	0.1643	15	0.4260	17
F3,3	0.7847	15	40	21	0.7445	16	0.1485	25	0.3459	25
F4,1	0.9563	1	70	10	0.9618	1	0.1843	8	0.4706	11
F4,2	0.7474	18	30	25	0.7510	15	0.1305	26	0.2709	28
F4,3	0.8135	10	12	29	0.6879	20	0.1147	28	0.2521	29
F5,1	0.9165	5	40	21	0.8305	7	0.1571	18	0.4317	15
F5,2	0.6591	25	40	21	0.6591	23	0.1571	17	0.4317	16
F6,1	0.6591	25	160	2	0.6591	23	0.2250	3	0.6488	3
F6,2	0.8126	11	60	13	0.8123	9	0.1691	13	0.4947	8
F6,3	0.7966	12	60	13	0.7964	10	0.1691	12	0.4947	9
F6,4	0.8522	7	80	7	0.8585	4	0.1890	7	0.5387	7
F7,1	0.7676	17	120	4	0.6751	22	0.2092	6	0.5627	6
F7,2	0.8320	9	75	8	0.7816	11	0.1824	9	0.4755	10
F7,3	0.5134	30	48	17	0.5683	30	0.1574	16	0.3807	24
F8,1	0.6600	23	48	17	0.6591	23	0.1552	21	0.4192	20
F8,2	0.7870	14	54	15	0.7637	13	0.1553	20	0.3860	22
F8,3	0.8430	8	54	15	0.8164	8	0.1553	19	0.3860	23
F8,4	0.7130	20	147	3	0.7019	17	0.2279	2	0.6963	2
F8,5	0.8830	6	162	1	0.8421	6	0.2299	1	0.7101	1
F9,1	0.5400	29	12	29	0.5961	29	0.1055	30	0.2369	30
F9,2	0.6600	23	35	24	0.6591	23	0.1684	14	0.4239	18
F9,3	0.4480	31	10	32	0.5440	31	0.0966	31	0.1849	31

According to Table 3, F8,5 with the RPN = 162 has been placed in the top priority and F6,1, F8,4 have been a stand in the second and third priority. As can be seen, since the RPN score, do not consider the weight of risk factors and relies merely on the multiplication of these factors' values, it failed to distinguish the priority of risks. F3,3 and F5,1 have different S, D and O values while having the same RPN scores. In this regard, various researchers have tried to modify or develop the FMEA technique using other methods such as MCDM techniques. Most of these, however, failed to preserve the merits of this traditional technique for the FMEA team, including compatibility with its opinions and practical applications. In other words, from the viewpoint of the FMEA team, a method can be efficacious in the risk assessment process that not only does not make unrealistic changes when the weight of risk factors is applied but also can create more separability among risk priorities. The results of two popular MCDM methods in Table 3 show that all of the methods have made a higher distinction than the traditional FMEA technique. However, ranking with multi-criteria decision-making methods has a high correlation with ranking with RPN (see Table 4). In contrast, the correlation between the proposed method and ranking based on multi-criteria decisions is very low. This is because decision-making methods do not take into account causal relationships between risk factors, so the score calculated for them is the abstract risk score without the involvement of other factors. In the real world, no risk factor is separate from other factors and factors affect each other, so ranking based on multi-criteria decision approaches cannot be real. While fuzzy cognitive mapping can easily consider the effect of these factors on each other, the reason for the ranking differences.

Table 4. Correlations between various used ranking methods.

	Multi-stage Delta-rule	RPN	Delta-rule	MOORA
RPN	0.227			
Delta-rule	0.937	0.350		
MOORA	0.159	0.944	0.281	
TOPSIS	0.195	0.883	0.320	0.936

Figure 6 represents the generated results to compare them from the separability perspective. In this figure, the normal value of the RPN index has been used to rank the results. Although it may have appropriate performance in generating different solutions at first glance, it has generated very close values, at least in the three areas. One of the important factors in analyzing risk factors is vivid ranking with various amounts that are not close to each

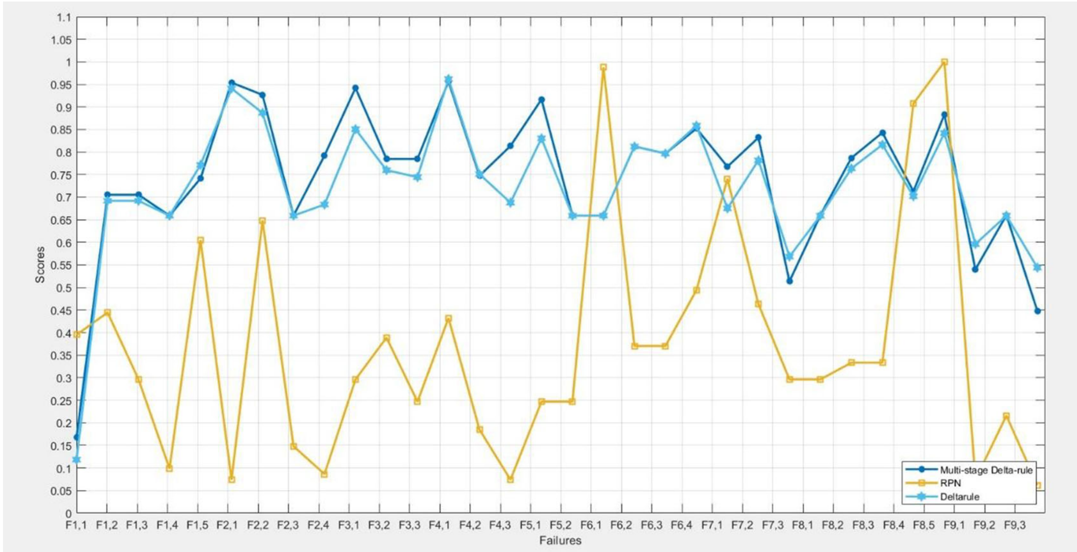

Figure 6. The dispersion of the generated results based on the various methods.

other. Experts should analyze the results with considerably high accuracy, and the close value of results can negatively affect the decision-making validation. The results should increase in a valid and secure interval to assist decision-makers in having a secure decision-making process by analyzing failures' ranking. Hence, the RPN factor is not a reliable method in this case.

On the other hand, both conventional FCM and MSFCM have an excellent performance in ranking the failures. Both of them can successfully generate solutions in a considerably safe interval with high separability. However, at some points, there are differences in ranking the failures. It is because of the different logic between these methods. The MSFCM possesses a potent logic in ranking the failures by considering the internal and external causal relationships between failures. As mentioned earlier, in some cases, some failures in previous stages may have an extremely conspicuous impact on the other failures in the next stages, and MSFCM can recognize this important issue. The more logical FCM, the more accurate the generated solutions. This strong capacity of the MSFCM could convince the decision-makers that this method is highly capable of ranking the failures.

6. Conclusion

An intelligent approach based on cause-and-effect relationships was proposed to assess and prioritize a manufacturing unit's risks in the production process of automotive brake pads. MSFCM was executed, and the final values for failures were obtained. The generated results were compared with the conventional FCM, with the Extended Delta rule algorithm and the RPN score for validating the proposed approach. It was inferred that both conventional FCM and MSFCM have excellent performance and similarities in ranking the failures. Both of them can successfully generate results in a considerably safe interval with high separability. Also, a comparison was conducted between the ranking results of both MSFCM and Delta rule learning algorithms. It was concluded that both methods' trend was very close, and both the highest and lowest failures scores are the same. Although RPN factor results showed some conformity with MSFCM and other methods in some areas, it was found as the unreliable method in this case. The main feature of this study is to map the processes of producing the brake pads in risk assessment and analysis. This map provides the cause-and-effect relationships in risk prioritization. In future endeavors, risks' reliability and uncertainty environment may be added to the analysis for better risk assessment.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability

All data used during this study are included in this published article.

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Appendix

The Appendix presents the matrix of initial weights of causal relationships among concepts. The weights of causal relationships among failures are determined based on experts' opinions (by FMEA CFT).

Appendix. The weight of causal relationships between failures.

	F1,1	F1,2	F1,3	F1,4	F1,5	F2,1	F2,2	F2,3	F2,4	F3,1	F3,2	F3,3	F4,1	F4,2	F4,3	F5,1	F5,2	F6,1	F6,2	F6,3	F6,4	F7,1	F7,2	F7,3	F8,1	F8,2	F8,3	F8,4	F8,5	F9,1	F9,2	F9,3
F1,1	0	0.8	0.8	0	0	0	0.5	0	0.6	0.5	0	0	0	0	0.7	0	0	0	0	0	0.3	0.4	0	0	0	0	0	0	0	0	0	0
F1,2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F1,3	0	0	0	0	0	0.3	0	0	0	0.2	0	0.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0	0	0	0	0	0
F1,4	0	0	0	0	0	0	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F1,5	0	0	0	0	0	0.3	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0	0	0	0	0
F2,1	-0.5	0	0	0	0.4	0	0.2	0	0	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F2,2	0	0	0	0	0	0.4	0	0	0	0	0	0	0.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F2,3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.3	0	0	0	0	0	0.1	0	0	0	0	0
F2,4	0	0	0	0	0	0.7	0.2	0	0	0.3	0	0	0	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F3,1	0	0	0	0	0	0.2	0	0	0	0	0	0	0.6	0.3	0	0.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F3,2	-0.5	0	0	0	0	0	0	0	0	0	0	0	0.4	0	0	0.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F3,3	-0.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.3	0	0.2	0	0	0	0
F4,1	0	0	0	0	0	0	0.3	0	0	0	0	0	0	0	0	-0.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F4,2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F4,3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F5,1	-0.7	0	0	0	0	0	0	0	0	0.3	0.4	0	0.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F5,2	0	0	0	0	0	0	0	0	0	0	0	0	0.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F6,1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.8	0.7	0.8	0	0	0	0	0	0	0	0	0	0	0
F6,2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F6,3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F6,4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0	0	0	0	0
F7,1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.6	-0.4	0	0	0	0	0	0	0	0
F7,2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F7,3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F8,1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.3	0	0.6	0	0	0
F8,2	-0.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F8,3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F8,4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4	0	0	0
F8,5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F9,1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F9,2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.3	0	-0.5
F9,3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0