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

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Complete List of Authors:	Mashhadi Keshtiban, Peyman ; Urmia University of Technology, Faculty of Mechanical Engineering Abbaspour Onari, Mohsen; Urmia University of Technology, Faculty of Industrial Engineering Jahangoshai Rezaee, Mustafa; Urmia University of Technology, Faculty of Industrial Engineering Shokri, Keyvan ; Urmia University of Technology, Faculty of Mechanical Engineering
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Abstract

When a risk occurs in a stage of 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. In this paper, an intelligent approach based on cause-and-effect relationships is proposed to assess and prioritize a manufacturing unit's risks. Sequential multi-stage Fuzzy Cognitive maps (MFCM) is used for drawing the map of risks. Then, the learning algorithm is implemented for learning the MFCM and finalizing the risks score. A case study on auto-parts manufacturing unit is applied to demonstrate the capabilities of the proposed approach.

Keywords: Risk assessment; Multi-stage fuzzy cognitive maps; Failure modes and effects analysis, Auto-parts manufacturing; Brake pads

1. Introduction

With the increasing growth of the automotive industry and the need for cars 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' mechanism 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, there will be less need for safety tools such as airbags. 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 brake pads with high quality 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 et al., 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 the stages of design and production (Liu et al., 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 of 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 and reach the customer, the conventional RPN method has been criticized extensively in the literature for many reasons (Liu et al., 2013). Liu et al. (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., 218). 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., 218).

Due to the mentioned problems 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) to consider causal relationships between different failures of the previous and subsequent stages and 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 identification, classification, analysis, and evaluation of hazards and their risks in the industries (Yousefi et al., 2018). 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 et al. (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 instead of RPN for each failure, and weights of the SOD factors and failure modes were computed by extended fuzzy Analytic Hierarchy Process (AHP) and Fuzzy Multiple Multi-Objective Optimizations by Ratio Analysis (MULTIMOORA) methods in a steel manufacturing industry. Baynal et al. (2018) proposed an integrated method combining Grey Relational Analysis (GRA) with FMEA to contribute to risk management activities by proposing solutions to assembly-line problems in an automotive manufacturing company and improve RPN. Foroozesh et al. (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 grey relational projection method to avoid the use of traditional RPN in a sheet steel production process of a steel manufacturing factory. Soltanali et al. (2020) 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 et al. (2020) 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.

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 FCM, and SOD factors are taken into account as the concepts of FCM. By training FCM, 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 et al., 2019). FCM possesses various applications in fields such as decision support system (Douali et al., 2015), environmental science (Demertzis et al., 2018), supplier selection problem (Alizadeh and Yousefi, 2019), time series prediction (Lu et al., 2014), medical diagnosis (Papageorgiou et al., 2015), etc. Furthermore, FCM can be implemented in risk assessment problems in various domains. Jamshidi et al. (2017) 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 Multi-Objective Optimization Based on Ratio Analysis (MOORA) for assessing and prioritizing occupational health and safety risks. Chen et al. (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. The MSFCM was introduced by Rezaee et al. (2017) for considering the impact of previous and subsequent failures on the current failures in a stage-by-stage perspective to enhance the accuracy of RPN scores. 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 Section 2, the implemented methods are introduced. In Section 3, the proposed approach to apply in the present study is described in detail. In Section 4, the studied case is presented. In Section 5, the results of the study are presented and analyzed. Finally, in Section 6, 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 present 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 identification, classification, analysis, and evaluation of 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' hand (Rezaee 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 et al., 2018):

1. Identifying the potential failure modes related to the production process.
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 from multiplying three factors of S, O, and D. These factors are illustrated in Table (1) and are ranked from 1 to 10. Hence, score 10 for risks in terms of severity means that it is extremely dangerous (hazardous without warning). Also, the score 10 in terms of occurrence means certain occurrence (failure is almost inevitable), and in terms of detection means undetectable risk (absolute uncertainty) (Yousefi et al., 2018).

Table 1. Traditional FMEA scales

Rating	S	O	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

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). FCM initially introduced by Kosko (1986) and has emerged as tools for modeling and studying the behavior of complex systems (Salmeron and Lopez, 2011). 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 $C_i, i = 1,...,N$ where N is the total number of concepts. Each concept acquires an activation value $A_i \in [0,1], i = 1,...,N$ 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):

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

$A_i^{(k+1)}$ 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).

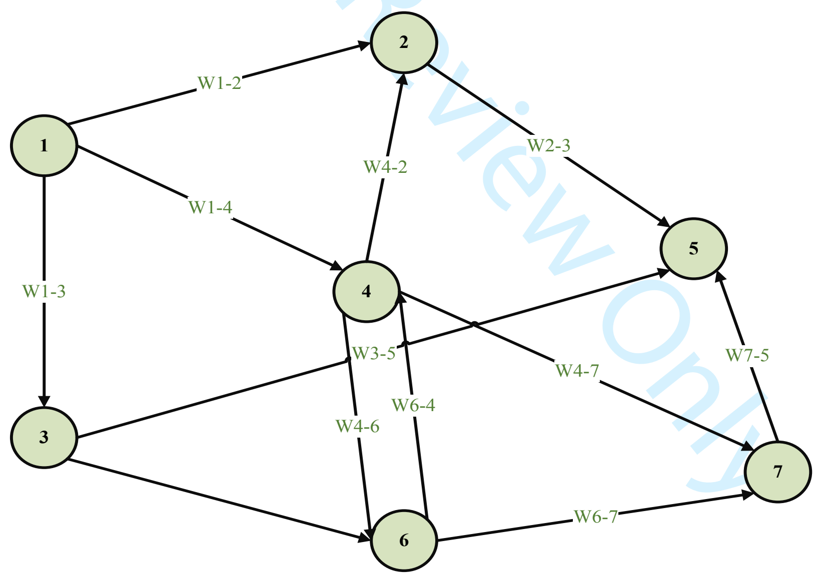

Figure 1. An FCM with seven nodes and 11 arcs

Rezaee 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 their nodes (concepts, components) have causal relationships with each other, and also have causal relationships with other nodes of the existing subsystems in a simultaneous manner (Rezaee et al., 2017). In the MSFCM, causal relationships between nodes in stages are internal or external. Internal-stage causal relationships are the arcs that connect considered FCM nodes in each stage to each other, and external-stage causal relationships are the arcs 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.

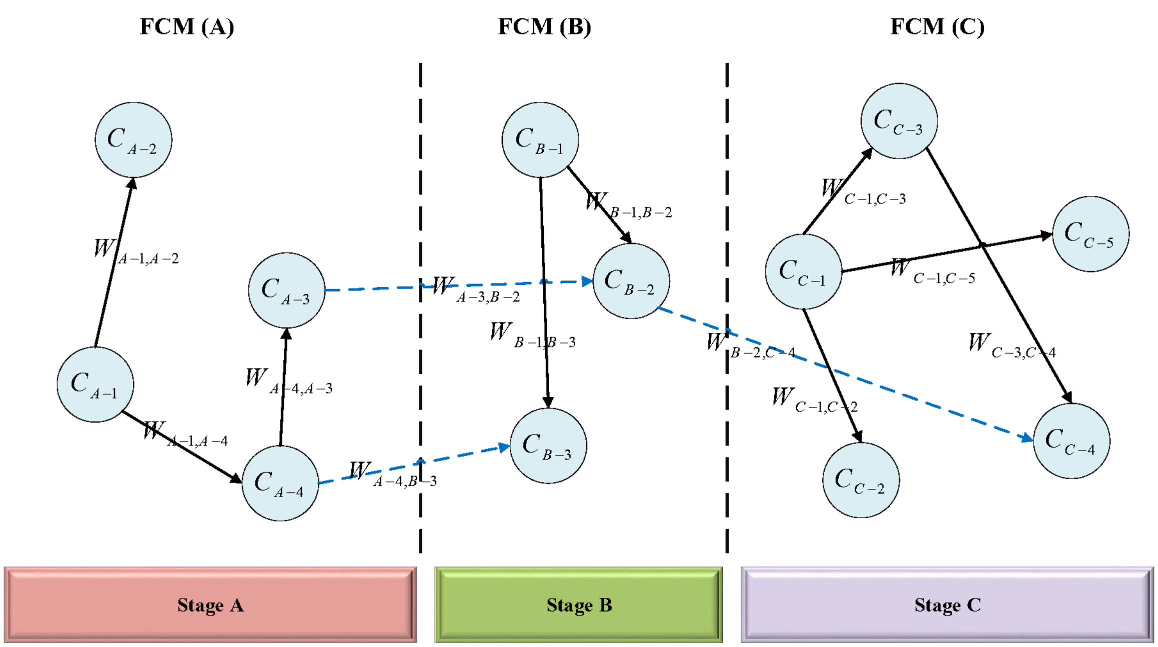

Figure 2. An MSFCM with three stages

2.3. Learning Algorithm Based on the Extended Delta Rule

In the FCM, precise estimation of map weights to increase their accuracy, improving the structure of the map, and reducing dependency on experts' opinions by learning algorithms are important issues. The Hebbian algorithm is one of the most popular FCM learning algorithms and possesses different types such as Differential Hebbian (DH), Active Hebbian (AH), Nonlinear Hebbian (NH), and Data-driven NH. One of the shortcomings of Hebbian algorithms is the lack of convergence in some situations (Rezaee et al., 2017). For this purpose, Rezaee et al. (2017) introduced the concept of the Extended Delta rule algorithm. 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 × N matrix as $A^{(0)}$ and an initial weights matrix, which is shown by N × N matrix as $W^{(0)}$ and represents the weights between system' 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 (arcs 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), which is the key calculation 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.

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

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 Delta rule is a supervised learning algorithm that is based on the existence of target values for training vectors. In the present study, the values of normalized RPN can be used as t_j. In Step 4, the learning algorithm based on 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 present study was set to be 0.00001 (Rezaee et al., 2018).

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

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

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

Step 4: Update the weights based on.

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).

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 Extended Delta rule (Rezaee et al., 2017)

3. MSFCM-PFMEA Approach

In this section, the implementation of the MSFCM method and PFMEA technique is presented to prioritize production process failures. 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 Cross-Functional Team (CFT). The output of this step is identifying 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. Moreover, these failures are connected by arcs that indicate the causal relationships between failures. Moreover, each of these factors is considered a particular concept for each failure to apply the triple factors of PFMEA for each failure. For instance, the first failure in an MSFCM and the probable relationship with other failures will have relationships with a definite weight of one 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.

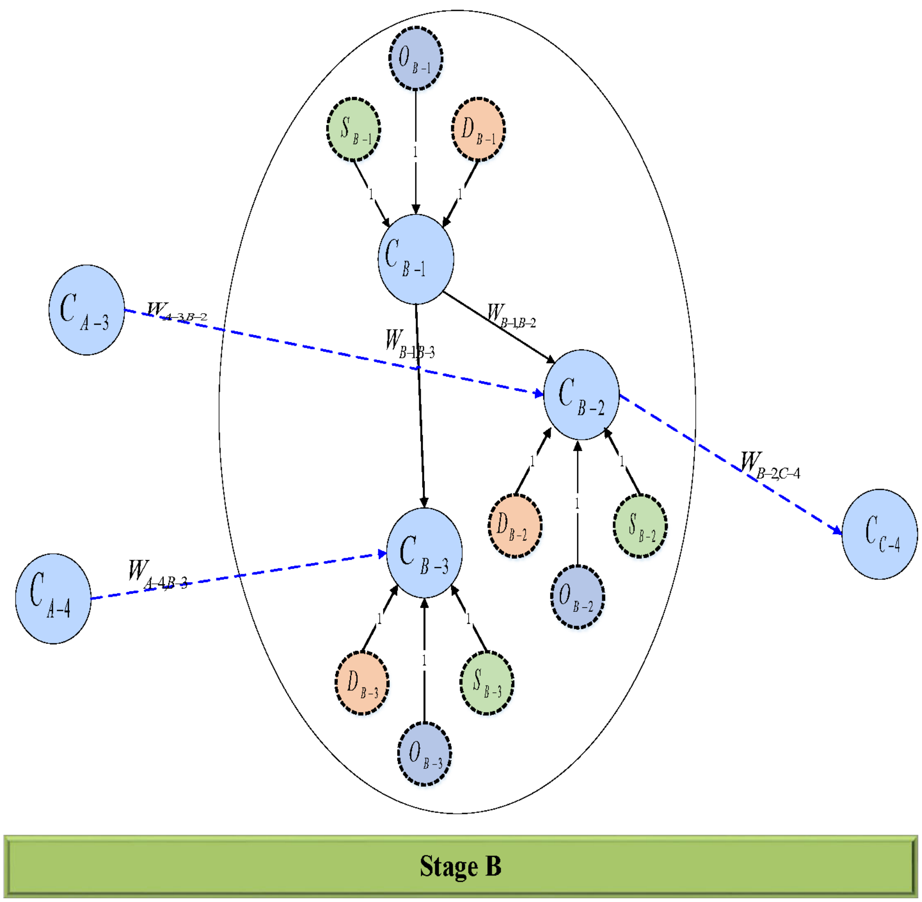

Figure 4. An overview of a stage of MSFCM-PFMEA approach

As shown in Figure (5), the jth stage of the MSFCM has been presented. Each concept (failure) has causal relationships with SOD factors allocated by the PFMEA team, and they are input concepts of failures. Moreover, similar to conventional FCM, each concept has causal relationships with each other. For instance, C_{j-1} is a failure, and SOD factors (S_{j-1}, O_{j-1}, D_{j-1}) are connected to that with the weight value of one. Also, C_{j-1} and C_{j-2} are failures that have causal relationships with each other and also other failures in the other stages. Then, 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: it is assumed that all concepts implicating the failures in this stage have the value of; normalized SOD factors for each failure of this stage are considered in the scenario, trained values of failures from the second stage to the next in the previous stage that has external-relationships with the studied stage are considered in the scenario definition.

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 the prioritization of 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 that represent failures and have external relationships with the next stages remain, and other nodes with all internal relationships are excluded from the next calculation. It should be explained that after the calculation of the score for each failure of the system, the prioritization of 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 present study, the manufacturing process of brake pads of Shabnam Lent Co. has been investigated to prioritize manufacturing failures in the production process. 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. At the next step, the prepared blocks are formed to the desired shape, 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.

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 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

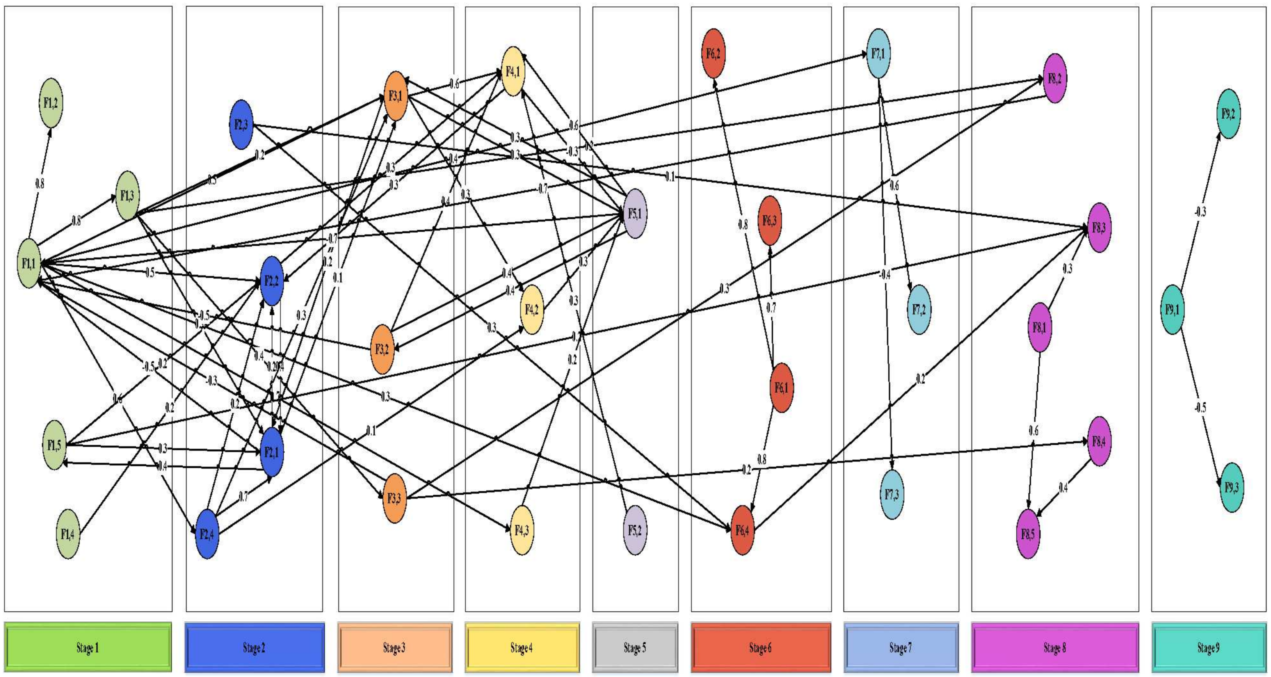

Figure 5. MSFCM for the studied case study

5. Analysis of the Results

In this section, the results of the proposed approach based on the MSFCM and the Extended Delta rule are analyzed. After determining the risks by the PFMEA 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, the weight of the relationships is assigned by the PFMEA CFT. Then, the MSFCM is executed, and the final values for failures are obtained. For validating the proposed approach, the generated results are compared with the conventional FCM with the Extended Delta rule algorithm and the RPN score.

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 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 PMFEA CFT. As can be seen in the second column of the Table (3), failures F8,5, F6,1, and F8,4 are considered as the most critical failures. There are conspicuous differences between the generated results between the two methods. It is due to the lack of the RPN index in considering the causal relationships between the failures in the various stages. It may exist causal relationships 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 occurring 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, F4,3, F9,1, and F9,3 have lower priority than other failures, which have notable differences with MSFCM.

In the last step, the MSFCM is compared with conventional FCM, which both of them apply the Extended Delta-rule as the learning algorithm. In the conventional FCM, internal and external relationships do not sense, and all of the failures are considered the whole. The purpose is to compare the impact of the multi-stage approach on the study with conventional FCM. In this approach, there are no remarkable differences between the generated solutions. In this approach, failures F4,1 and F2,1 have the highest ranking between the failures and have an identical performance with MSFCM. However, in this approach, the failure of F2,2 has the third highest-ranking between failures, which has different results compared with MSFCM, which is due to the conventional perspective, which has been implemented on the FCM. There are no differences between the least important failures among two algorithms. As can be seen, 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.

Table 3. The generated results based on the various methods

	Multi-stage Delta-rule	Ranking	RPN	Ranking	Delta-rule	Ranking
F1,1	0.1674	32	64	11	0.1186	32
F1,2	0.7053	21	72	9	0.692	18
F1,3	0.7053	21	48	17	0.692	18
F1,4	0.6591	25	16	27	0.6591	23
F1,5	0.7416	19	98	6	0.7715	12
F2,1	0.9539	2	12	29	0.9408	2
F2,2	0.9266	4	105	5	0.8867	3
F2,3	0.6591	25	24	26	0.6591	23
F2,4	0.7922	13	14	28	0.6837	21
F3,1	0.9418	3	48	17	0.8507	5
F3,2	0.7847	15	63	12	0.7598	14
F3,3	0.7847	15	40	21	0.7445	16
F4,1	0.9563	1	70	10	0.9618	1
F4,2	0.7474	18	30	25	0.751	15
F4,3	0.8135	10	12	29	0.6879	20
F5,1	0.9165	5	40	21	0.8305	7
F5,2	0.6591	25	40	21	0.6591	23
F6,1	0.6591	25	160	2	0.6591	23
F6,2	0.8126	11	60	13	0.8123	9
F6,3	0.7966	12	60	13	0.7964	10
F6,4	0.8522	7	80	7	0.8585	4
F7,1	0.7676	17	120	4	0.6751	22
F7,2	0.832	9	75	8	0.7816	11
F7,3	0.5134	30	48	17	0.5683	30
F8,1	0.66	23	48	17	0.6591	23
F8,2	0.787	14	54	15	0.7637	13
F8,3	0.843	8	54	15	0.8164	8
F8,4	0.713	20	147	3	0.7019	17
F8,5	0.883	6	162	1	0.8421	6
F9,1	0.54	29	12	29	0.5961	29
F9,2	0.66	23	35	24	0.6591	23
F9,3	0.448	31	10	32	0.544	31

Figure (6) represents the generated results to compare results from the separability perspective. In this figure, the normal value of the RPN index has been used to rank the results. Although at first glance, it may have appropriate performance in generating different solutions and has generated very close amounts, at least in the three areas. One of the important factors in analyzing risk factors is vivid ranking with various amounts that they are not close to each other. Experts should analyze the results with considerably high accuracy, and the close amount 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 results 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 results. This strong capacity of the MSFCM could convince the decision-makers that this method is highly capable of ranking the failures.

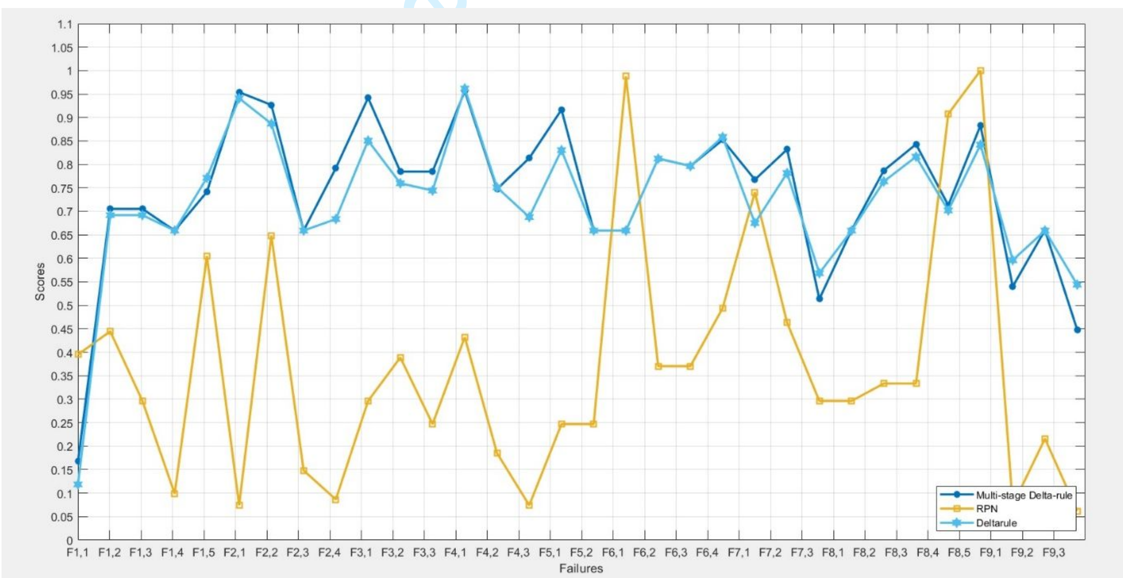

Figure 6. The dispersion of the generated results based on the various methods

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. For validating the proposed approach, the generated results were compared with the conventional FCM, with the Extended Delta rule algorithm and the RPN score. It was inferred that, both conventional FCM and MSFCM have an excellent performance and similarity in ranking the failures. Both of them can successfully generate results in a considerably safe interval with high separability. Also, comparison was done between the ranking results of both MSFCM and Delta rule learning algorithm. It was concluded that not only the trend of both methods was very close but also both highest and lowest failures scores are the same. Although RPN factor results showed some conformity with MSFCM and other methods in some areas but, it was found as 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 the future endeavors, for better risk assessment, the reliability and uncertainty environment of risks may be added to analysis.

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

Declarations

Ethics approval: For this type of study, formal consent is not required.

Consent to participate: The authors voluntarily agreed to participate in this research study.

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Competing interests: The authors declare no competing interests.

Appendix

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

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