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Research

An Alternative Evaluation of FMEA: Fuzzy ART Algorithm

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Failure Mode and Effects Analysis (FMEA) is a technique used in the manufacturing industry to improve production quality and productivity. It is a method that evaluates possible failures in the system, design, process or service. It aims to continuously improve and decrease these kinds of failure modes. Adaptive Resonance Theory (ART) is one of the learning algorithms without consultants, which are developed for clustering problems in artificial neural networks. In the FMEA method, every failure mode in the system is analyzed according to severity, occurrence and detection. Then, risk priority number (RPN) is acquired by multiplication of these three factors and the necessary failures are improved with respect to the determined threshold value. In addition, there exist many shortcomings of the traditional FMEA method, which affect its efficiency and thus limit its realization. To respond to these difficulties, this study introduces the method named Fuzzy Adaptive Resonance Theory (Fuzzy ART), one of the ART networks, to evaluate RPN in FMEA.

KEY WORDS: Fuzzy Adaptive Resonance Theory (Fuzzy ART); Failure Modes and Effect Analysis (FMEA); clustering analysis

INTRODUCTION

Failure Mode and Effect Analysis (FMEA) first emerged from studies done by NASA in 1963; it was then applied to the car manufacturing industry. The FMEA method is based on a session of systematic brainstorming for uncovering the failures that might occur in a system or in a process.

Traditionally, when performing an FMEA, three indices have been used: occurrence (O), severity of the associated effects (S) and detection (D). Typically, they are scaled with an integer number from 1 to 10. Increasing number causes unfavorable effect. The product of the three indices discussed gives a risk degree, known as risk priority number (RPN).

This study focuses on FMEA from the point of a new perspective based on Fuzzy Adaptive Resonance Theory (Fuzzy ART) neural networks. This paper is structured into seven sections. The second section mentions FMEA and its shortcomings. The third section describes Adaptive Resonance Theory (ART) neural networks. The fourth section explains Fuzzy ART, which is one of the ART networks. Fuzzy ART is applied

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to FMEA in the fifth section. Sample problem and solution of a real case is given in the sixth section. It is followed by a discussion in the seventh section and conclusions in the eighth section.

FMEA AND ITS SHORTCOMINGS

FMEA is a reliability tool, which requires identifying failure modes of a specific product or system, their frequency and potential causes.

It is a design discipline used extensively in the aerospace and automotive industry. Every possible failure that can occur in a specific design is considered, and the effects of each failure on the operation of the overall system are calculated, in order to identify severe, frequently occurring failures, and to eradicate them from the design if possible. FMEA can be performed hierarchically, with the failure modes at the lower level producing effects at the higher level[1].

For a generic design, after the identification of failure modes, effects and causes of a possible occurrence, the RPN is calculated. RPN is an index that expresses the risk level priority associated with each failure mode. In the traditional FMEA approach, the RPN index is determined by calculating the product of the three indices: severity, occurrence and detection[2]:

The RPN is calculated for every cause of failure considered and is a function of the following three ratings:

$$\mathrm{RPN} = S \cdot O \cdot D^3$$

where severity (S) is an estimate of the severity of the worst effect of failure, occurrence (O) an estimate of the likelihood of the occurrence of the failure cause and detection (D) an estimate that reflects how difficult it is to detect a given failure cause.

The main objective of FMEA is to discover and prioritize the potential failure modes that could have a detrimental effect on the system and its performance. The results of the analysis help managers and engineers to identify the failure modes and their causes and correct them during the stages of design and production.

In the current FMEA practice, engineers should assign a threshold RPN value to classify failure modes. In classical FMEA, precautions are taken for all failure modes that are above 100 RPN values. This threshold strongly defies classification. For instance, a failure mode with RPN = 100 is to be considered as ‘corrective action required’. But another failure mode with RPN = 98 is classed as ‘consider corrective action’.

For all failure modes over the determined threshold value level, corrective precautions should be confirmed. This means that if the failure mode to be corrected is increased, the cost will increase at the same per cent.

In FMEA corrective actions are taken to fix the failure modes with higher RPN values. However, sole reliance on RPN may mislead the engineers and waste valuable resources by fixing the non-critical failures and letting the critical failures go unnoticed. For instance, a failure with $(S, O, D) = (6, 1, 3)$ will have an RPN = 18, and another failure mode with $(S, O, D) = (4, 2, 3)$ will have an RPN = 24. Although it is arguable, as per traditional practice, the priority will be to fix the second failure mode even when the severity of the first failure mode is much higher than the second one[4,5]. In addition, various sets of input terms, namely the probability of occurrence, the severity and the detection, may produce an identical value, whereas the risk implication may be totally different and may result in high-risk events going unnoticed[6].

Another point worth mentioning is that some numbers between 1 and 1000 cannot be obtained from the product of three risk factors, as is the case of the numbers that have a prime factor greater than 10[7].

ART NEURAL NETWORK

The ART is an outstanding example of how designing artificially intelligent systems and understanding the brain may benefit from each other. ART is inspired by the recurrent structure of information processing in

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the cortex and deeper lying structures. The fact that ART was inspired by recurrent brain structures should not be confused with issues of implementing ART on a computer[8].

ART originated from an analysis of human cognitive information processing and sTable coding in a complex input environment. An evolving series of ART neural network models have added new principles to the earlier theory and have realized these principles as quantitative systems that can be applied to problems of category learning, recognition and prediction[9].

ART networks are widely used in clustering and classification problems. A clustering algorithm takes as input a set of input vectors and gives as output a set of clusters and a mapping of each input vector to a cluster. Input vectors that are close to each other according to a specific similarity measure should be mapped to the same cluster. Clusters can be labeled to indicate a particular semantic meaning pertaining to all input vectors mapped to that cluster.

The classical ART clustering algorithms are: ART1 (it clusters binary input patterns and is the basic ART network); ART2 (it clusters real-valued input patterns); ART2A (fast version of ART2); ART3 (this network is an ART extension that incorporates 'chemical transmitters' to control the search process in a hierarchical ART structure); Fuzzy ART (incorporates computations from fuzzy set theory into ART1. It uses Fuzzy AND operator instead of the crisp operator) architecture[10,11].

ART adapts to new inputs indefinitely. New categories can be formed when the environment does not match any of the stored patterns; however, the environment cannot change stored patterns unless they are sufficiently similar.

A typical ART network consists of two layers: an input layer and an output layer. There are no hidden layers. The network dynamics are governed by two subsystems: an attention subsystem and an orienting subsystem. The attention subsystem proposes a winning neuron (or category) and the orienting subsystem decides whether to accept it or not[11].

FUZZY ART

Fuzzy ART is the most recent adaptive resonance framework that provides a unified architecture for both binary and continuous value inputs. Fuzzy ART operations reduce to ART1 (which accepts only binary vectors) as a special case. The generalization of learning both analog and binary input patterns is achieved by replacing the appearance of the logical AND intersection operator ($\cap$) in ART1 by the MIN operator ($\wedge$) of fuzzy set theory[12].

Fuzzy ART neural network involves several changes to ART1: (1) non-binary input vectors can be processed; (2) there is a single weight vector connection and (3) in addition to vigilance threshold (ρ), two other parameters have to be specified: a choice parameter (α) and a learning rate (β)[13].

Literature review of Fuzzy ART

Several researchers have investigated applications of Fuzzy ART networks. Carpenter *et al.*[14] developed Fuzzy ART algorithm. Huang *et al.*[15] presented some important properties of the Fuzzy ART. Munoz[16] proposed a method that uses a hierarchical model made up of Fuzzy ART neural network. Blume and Esener[17] proposed an alternate approach achieving choice and matching functions at the same layer. Georgiopoulos *et al.*[18] explained the properties of learning of a Fuzzy ART variant. Chung *et al.*[19] applied the Fuzzy ART theory for fuzzy clustering in the input/output spaces. Tomida *et al.*[20] presented gene expression analysis using Fuzzy ART. Kim *et al.*[21] developed a robust pattern recognition model for using Fuzzy ART algorithm. Tomida *et al.*[22] applied Fuzzy ART for analyzing the time series expression data during sporulation of *Saccharomyces cerevisiae*. Anagnostopoulos and Georgiopoulos[23] introduced novel geometric concepts in the original framework of Fuzzy ART and Fuzzy ARTMAP. Kato *et al.*[24] applied heat shock to genes. Lubkin and Cauwenberghs[25] presented a mixed mode VLSI chip that implements models of Fuzzy ART and LVQ. Park and Suresh[26] applied Fuzzy ART and hierarchical clustering to part-machine grouping. Gomez and Chesnevar[27] applied Fuzzy ART neural network to pattern classification. Pacella *et al.*[12] used a Fuzzy

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ART neural system for manufacturing quality monitoring. Peker and Kara[28] explained a parameter setting of the Fuzzy ART neural network to part-machine cell formation problem. Cinque *et al.*[29] proposed a modified Fuzzy ART and its application to image segmentation. Lopes *et al.*[30] applied Fuzzy ART&ARTMAP neural network to the electric load-forecasting problem. Dagher[10] presented the geometrical properties of Fuzzy ART and Fuzzy ARTMAP networks.

An additional desirable property of Fuzzy ART is that, due to the simple nature of its architecture, responses of the neural network to input patterns are easily explained, in contrast to other models, where in general it is more difficult to explain why an input pattern produces a specific output. Significant insight has been gained in the past by attributing a geometrical interpretation to the Fuzzy ART categories and, recently, novel geometric concepts have been introduced in the original framework[12].

Fuzzy ART is an unsupervised learning algorithm using structure calculus based on fuzzy logic. And it is based on ART algorithm. Fuzzy ART neural network was introduced by Carpenter *et al.* in 1991[30]. Lee and Fischer[31] proposed a new part family classification system, which incorporates image processing techniques and a modified Fuzzy ART neural network algorithm.

FMEA USING FUZZY ART

In this study the Fuzzy ART algorithm is applied to FMEA, and RPNs are clustered using Fuzzy ART. The Fuzzy ART model for FMEA is shown in Figure 1.

$x_{i,j}$ is the input value of the model, C_s represents the failure mode classes and $w_{i,j,s}$ represents the weights between Layers 1 and 2. It also determines the membership of each input values at Layer 1 to the classes at Layer 2.

Severity, occurrence and detection values constituting RPN value are evaluated independently for each input. Although RPN values are equal to each other, FMEA values are evaluated separately with severity, detection and occurrence values rather than with a multiple of these parameters.

Thus, RPN values compose inputs and each input in its own is presented as S, O and D to the system. In each case, an input composed of three data (S, O, D) is presented to the system by efficient parameter results obtained from application of FMEA on test problems and similar inputs are clustered according to the three parameters.

The step-by-step illustration of Fuzzy ART FMEA methodology is as follows:

Step 1—Normalization: Each of the three input values $I_{(i,j)}$, which are severity (S), occurrence probability of failure (O) and detection (D), is normalized by the following equation:

$$\mathrm{NI}_{i,j} = \frac{I(i,j) - \min(j)}{\max(j) - \min(j)} \tag{1}$$

where i: $1 \to n$, n is the maximum failure mode number, j: 1: severity, 2: occurrence and 3: detection $\mathrm{NI}_{i,j}$ the normalized input value.

Step 2—Determining parameters: The values of choice (α), vigilance (ρ) and learning ratio (β) parameters should be assigned. Parameters' intervals for any Fuzzy ART problem are as follows:

- Vigilance threshold ρ is responsible for the number of classes $(0<\rho<1)$.
- Choice parameter α is effective in class selection $(0<\alpha\leq 1)$.
- Learning rate β controls pace of classification $(0<\beta\leq 1)$.

Choice (α), vigilance (ρ) and learning ratio (β) parameters are defined by the user. Parameter selection is specific to the problem type.

Step 3—Determination of initial weights for Fuzzy ART FMEA: Initially all weights are taken equally at 1. The number of the class C_s is set as 1:

$$w_{i,j,s}(0) = 1 \quad \text{and} \quad s = 1 \quad \text{for } \forall i, j$$

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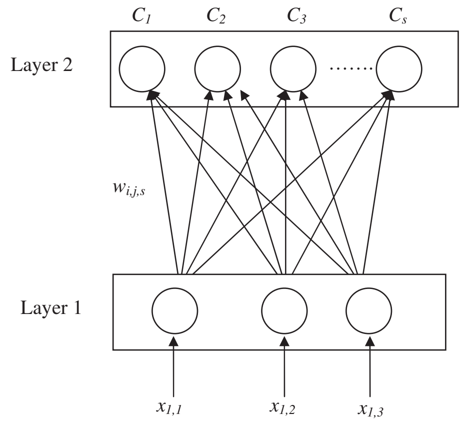

Figure 1. Modeling FMEA methodology by Fuzzy ART

Step 4—Representation of input values to network: Input vector (x) (normalized values of input triple) is designated to network:

$$x: \quad \forall x_{i,j} \in (0,1]$$

Step 5—Computation of choice function value: Choice function $T_{i,j,s}$ is defined with the following equation:

$$T_{i,s}(\mathrm{NI}) = \frac{\sum_{j=1}^{3} (\mathrm{NI}_{i,j} \wedge w_{i,j,s})}{\alpha + \sum_{j=1}^{3} w_{i,j,s}} \tag{2}$$

where '$\wedge$' is fuzzy 'AND' operator and $(x \wedge y) = \min(x, y)$.

Step 6—Selection of maximum choice function value (T^*): The highest of the choice function values is selected:

$$T^* = \max\{T_{i,s} : s = 1, 2, \ldots, m\} \tag{3}$$

Step 7—Matching test: Matching test determines the appropriate class for the input. Matching function is calculated with the following equation:

$$M_{i,s}(T^*) = \frac{\sum_{j=1}^{3} (\mathrm{NI}_{i,j} \wedge w_{i,j,s})}{\sum_{j=1}^{3} \mathrm{NI}_{i,j}} \tag{4}$$

If $M_{i,s} \geq \rho \Rightarrow T_{i,s}$ is passing the test. Therefore, the ith failure mode is added to the existing class C_s and then go to step 9.

If $M_{i,s} < \rho$ $T_{i,s}$ is not passing the test, then go to step 8.

Step 8—Resetting: Set the choice function value as $T_{i,s} = -1$ and go back to step 6. Control the next highest $T_{i,s}$ value. In this way, matching test continues for all of the $T_{i,s}$ values.

If none of $T_{i,s}$ pass the test a new class is created for the existing input. Therefore, the ith failure mode is added to the new class C_{s+1}. Go to step 4 and continue with the next input.

Step 9—Updating weights: According to the following equation, input weights of the existing input are updated as:

$$w_{i,j,s}^{(new)} = \beta(\mathrm{NI}_{i,j} \wedge w_{i,j,s}^{(old)}) + (1-\beta) w_{i,j,s}^{(old)} \tag{5}$$

Step 10—Repeat: The algorithm continues with the next input at step 4. Stop if all data are allocated to s different classes.

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Step 11—Prioritization of classes: Obtained failure classes should be prioritized. Arithmetic mean of the input values in each class is used for prioritization. Classes are ranked according to their priority and labeled.

To perform the above-mentioned Fuzzy ART FMEA methodology, a computer program coded in MATLAB 7.1 is required.

SAMPLE PROBLEM AND SOLUTION

To test the contribution of our approach, the same real-life problem given in Table I is solved by using both classical FMEA method and the proposed Fuzzy ART FMEA algorithm.

Problem: The data are taken from an international motor company's plant in Turkey. Attention is particularly devoted to a shock absorber assembly line. Shock absorbers are components that absorb or dissipate energy. They are an important part of automobile and motorcycle suspensions, aircraft landing gear, and also the supports for many industrial machines. Although they are used in all machines that are work impacted, they are most commonly used in vehicles. Without shock absorbers, vehicles would have a bouncing ride, as energy is stored in the spring and then released to the vehicle, possibly exceeding the allowed range of suspension movement. Shock absorbers allow the use of lower rate springs while controlling the rate of suspension movement in response to bumps. They also, along with hysteresis in the tire itself, damp the motion of the unsprung weight up and down on the springiness of the tire.

A shock absorber in a car is designed to damp the oscillations of the suspension springs in the car. Without this damping after a car passes over a bump, it will oscillate up and down many times rather than just once. Damping in shock absorbers is obtained by forcing a piston to move through a liquid-filled cylinder with an appropriate amount of fluid flow through or around the cylinder. This provides a drag force that is approximately proportional to the speed at which the piston moves.

Shock absorbers are not only useful components for vehicles' comfort, but they also ensure the roadholding of the tires. A good shock absorber prevents skidding on a road curve. It both redunds the traction and shortens the stopping distance while braking by providing strong holding and by preventing the tires to bounce up and down.

The cylinder part of the shock absorber's external body has two layers and the spaced portion is the auxiliary grease retainer. A protective dust tube extending to the top of the cylinder and a piston functioning in the cylinder are tied to the piston bar. The structure of a common shock absorber and its direction of motion is shown in Figure 2.

Introduction of processes: Related processes are realized in the following six lines:

Pipe line: Reserve, pressure and dust extraction pipes are cut at the guillotine and revolver lathe. Burrs are beveled.

Welding line: Welding of spring flat and bracket is done with argon welding machines for subassembly group and brackets are drilled with eyeletting machines.

Component preparation line: At this line, welding of the components that composed the assembly groups is done with projection welding machines.

Shaft preparation-chrome line: Various types of shafts are cut and toughened by the machines at this line. Lower and upper copies are obtained from turning lathe and are ground at a grinder before chrome plating. Then, chrome plating shafts are ground to become ready for assembly.

Assembly line: Base valve assembly group, upper valve assembly group pressure pipe and lower assembly group are met to constitute the final product.

Painting–packaging line: Final product that exits from the assembly is painted with electrostatics wet paint and prepared for transhipment by fixing packet parts after it is phosphated.

Process FMEA at assembly line: In this part, the systematic manner of displaying potential defect types related to assembly process, potential causes of defects and their effects on customers and the analytical way of determining important process variables that are necessary for controls in displaying and preventing defect conditions are examined.

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Table I. Sample problem data

Part name	Process function	Potential failure mode	Potential effects of failure	Potential causes of failure	Current controls	*S*	*O*	*D*	RPN	Recommended actions and status	Actions taken	*S*	*O*	*D*	RPN	Possible activity
Subassembly group	Cleaning subassembly group with air brush	Burr on metal	Burrs remaining at subassembly group damaged the shock absorber by moving into the parts of the valve	Insufficient air brush system		9	8	7	504	Changing the brushes	Brushes are changed	9	3	7	189	Method and product development
Pressure pipe	Pressure pipe calibration	Scratching interior surface of the pressure pipe	Performance changes in time	Penetrating foreign substance between ball and pressure tube because of unsuitable environment conditions	None	5	6	6	180	Preventing entrance of burr spreading from pah kırma mill next to gauge mill to oily environment where gauge is made	Placing a disc to provide safety between calibration bench and chamfer bench	5	4	6	120	Management
Suction valve	Suction valve to shaft assembly	Suction valve to shaft assembly is skipped	Performance of shock absorber changes	Operator fault	Performance test	5	5	5	125	Job enrichment by relocating the operators	Decided to relocate the operators by 2-h periods	5	4	4	80	Method and product development
Lubricant retainer seal	Lubricant retainer seal to shaft assembly	Reverse fixing lubricant retainer seal to shaft	Oil leakage	Operator fault		9	3	7	189	Job enrichment by relocating the operators	Decided to relocate the operators by 2-h periods	9	2	7	126	Method and product development
Pressure pipe	Filling grease in pressure pipe	Filling insufficient amount of grease in pressure pipe	Shock absorber may not work	Operator fault		8	2	5	80			8	2	5	80	
Serration disc	Serration disc assembly	Assembly of serration disc is skipped	Unstable performance	Operator fault	Performance test	2	8	3	48			2	8	3	48	
Valve spring	Valve spring assembly	Valve spring assembly is skipped	Shock absorber does not work	Operator fault		10	1	1	10			10	1	1	10	
Ring-type shim	Ring-type shim assembly	Ring-type shim assembly is skipped	Unstable performance	Operator fault	Performance test	8	3	5	120	Job enrichment by relocating the operators	Decided to relocate the operators by 2-h periods	8	1	5	40	Method and product development
Valve body	Valve body assembly	Valve body assembly is skipped	Shock absorber does not work	Operator fault	Valve assembly cannot be done	8	1	5	40			8	1	5	40	
Split ring	Split ring to shaft assembly	Split ring to shaft assembly is skipped	Performance failure	Operator fault	Performance test	7	3	5	105	Job enrichment by relocating the operators	Decided to relocate the operators by 2-h periods	7	1	5	35	Method and product development
Torque ring-type shim	Torque ring-type shim assembly	Assembly of torque ring-type shim is skipped	Not a problem	Operator fault	Control instruction	4	4	3	48			4	4	3	48	

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Table I. *Continued*

Part name	Process function	Potential failure mode	Potential effects of failure	Potential causes of failure	Current controls	*S*	*O*	*D*	RPN	Recommended actions and status	Actions taken	*S*	*O*	*D*	RPN	Possible activity
Split ring	Split ring to shaft assembly	Split ring to shaft end assembly is more than once	Performance failure	Operator fault	Performance test	7	3	5	105	Job enrichment by relocating the operators	Decided to relocate the operators by 2-h periods	7	1	5	35	Method and product development
Spring flat	Spring flat assembly	Spring flat assembly is skipped	Shock absorber does not work	Operator fault		10	1	1				10	1	1	10	
Collar nut	Applying collar nut	Burr on collar nut	Burrs existing when collar nut squeezes reduce the shock absorber performance by entering between valve parts	Torque is 12.5 kg m	None	9	5	6	270	By making machine efficiency analysis for used torque gun, its capability will be measured and statistical quality control will be applied	A new torque gun is bought	9	3	4	108	Quality assurance
Shaft–thimble	Shaft–thimble assembly	Shaft–thimble assembly is weak	Possibility of closing thimble with the hard stroke	Welding value is 4.9 bar	100% resource control	9	1	1	9			9	1	1	9	
Opening bumper	Opening bumper to shaft assembly	Opening bumper is skipped in shaft rotary table assembly	Made noise when vehicle drops to cavity	Operator fault	Control	8	3	7	168	Job enrichment by relocating the operators at assembly	Decided to relocate the operators by 2-h periods	8	1	7	56	Method and product development
Subassembly group	Filling grease in subassembly group and assembly to upper assembly group	Filling grease in subassembly group and in upper assembly group oil amount is 249 cm^3	Performance changes in time	Operator forgets to fill grease	Control instruction	8	2	5	80			8	2	5	80	
Valve spring	Valve spring	Valve spring is slack	Shock absorber creates noise in time	Torque is 12.5 kg m	None	4	5	6	120	Sufficiency of torque gun will be measured	Torque gun was renewed	4	3	4	48	Quality assurance
Upper assembly group	Filling grease in subassembly group and assembly to upper assembly group	Filling grease in subassembly group and in upper assembly group oil amount is 262 cm^3	Shock absorber cannot close completely	Operator fills excessive grease	Control instruction	8	2	5	80			8	2	5	80	

Table I. *Continued*

Part name	Process function	Potential failure mode	Potential effects of failure	Potential causes of failure	Current controls	*S*	*O*	*D*	RPN	Recommended actions and status	Actions taken	*S*	*O*	*D*	RPN	Possible activity
Shaft bearing–bush	Shaft bearing–bush component assembly	Inaccurate shaft bearing–bush assembly is skipped	Operation cannot be done	Operator fault	100% control	3	1	9	27			3	1	9	27	
Inlet valve spring–shaft	Inlet valve spring–shaft assembly	Inlet valve spring to shaft is skipped	Performance of shock absorber changes	Operator fault	Performance test	4	8	3	96			4	8	3	96	
Suction valve-ring-type shim	Suction valve-ring-type shim assembly	Excessive ring-type shim assembly	Performance changes	Operator fault	Performance test	8	3	5	120			8	1	5	40	
Valve body	Valve body assembly	Valve body assembly is fixed reversely	Shock absorber does not work	Operator fault	Valve assembly cannot be done	8	1	5	40			8	1	5	40	
Imperviousness disc	Imperviousness disc assembly	Imperviousness disc assembly is skipped	Unstable performance	Operator fault	Performance test	8	1	10	80			8	1	10	80	
Pressure pipe	Filling in pressure pipe	Filling insufficient amount of grease in pressure pipe	Shock absorber may not work	Machine adjustment failure	Shift control	8	2	5	80			8	2	5	80	
Collar nut	Applying collar nut	Applying locking liquid to valve spring assembly	Skipped	Shock absorber damages in time	100% control	9	1	1	9			9	1	1	9	
Upper assembly group	Plastering	Insufficient plastering	Oil leakage	Manometer pressure is 5 bar		9	4	9	324	Periodical maintenance and calibration of manometer will be done	Manometer was calibrated	9	2	9	162	Quality assurance
Upper assembly group	Plastering	Excessive plastering	Felt deformation	Manometer pressure is 5 bar		9	4	9	324	Periodical maintenance and calibration of manometer will be done	Manometer was calibrated	9	2	9	162	Quality assurance
Shaft bearing–bush	Shaft bearing–bush assembly	Bush depth is equal to 1.2 at the shaft bearing–bush assembly	Made noise in time	Press pressure is low	Lot control	3	1	9	27			3	1	9	27	

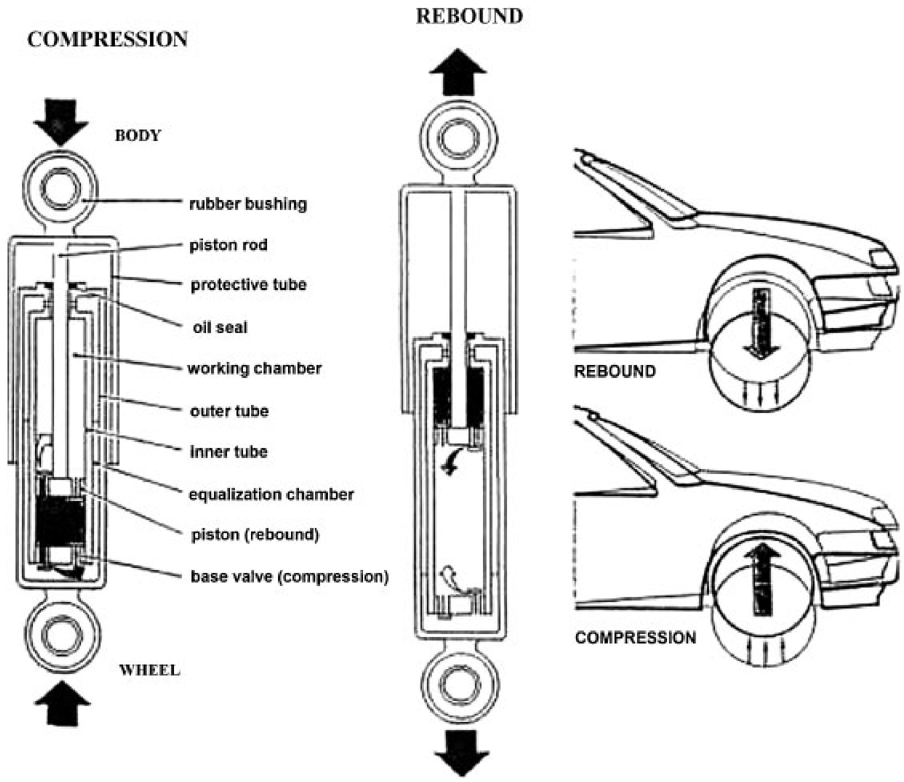

Figure 2. The structure of a common shock absorber and its direction of motion

Application is related to assembly of the front shock absorber used in automobile firms. The card seen in Table I is the standard FMEA card used in front shock absorber assembly. Process FMEA study is realized by using these cards.

The failures at the assembly line are analyzed and 29 different failure modes are identified. For instance, 1 numbered potential failure mode is burr on metal. The burr that remains at the subassembly group potentially breaks down the shock absorber in course of time and causes the inability of the air brush system. The plant's experts are assigned severity, occurrence and detection values to each failure mode using (1–10) scale.

Classical FMEA solution: For each failure mode $\mathrm{RPN} = S \cdot O \cdot D$ is calculated. Failure modes are classified into three classes according to the equations below. The classification results are given in Table II.

$\mathrm{RPN} > 100$ Class 1

$40 < \mathrm{RPN} < 100$ Class 2

$\mathrm{RPN} \leq 40$ Class 3

Fuzzy ART solution: The main characteristic of Fuzzy ART methodology is adaptation. Algorithm controls the similarity between input values. By considering the vigilance parameter, it defines the membership of input values to the classes. In this study, the purpose of the application of Fuzzy ART algorithm is to classify all the failure modes according to their similarities with the aid of the vigilance parameter.

Owing to the facility of adaptation and checking the similarity between the inputs, this method can be easily applied to all sectors such as production and service. In addition, the size of the sector does not matter. Likewise, it is possible to perform the algorithm to the system, design, process and service FMEAs.

The data are collected and severity, occurrence and detection risk factors are determined as in classical FMEA.

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One of the most important advantages of the method is that it can be easily applied regardless of the size of the data. The Fuzzy ART FMEA method does not require any expert for its application; it can be applied easily in practice with the aid of a small program.

The application of the proposed Fuzzy ART FMEA algorithm is shown stepwise for the first three failure modes:

Step 1: All of the 29 failure mode data are normalized using (1).

$NI_{1,1}=0.875$, $NI_{1,2}=1.0$, $NI_{1,3}=0.6667$ are calculated for the first failure mode ($S=9$, $O=8$, $D=7$).

Step 2: Parameters are selected for this problem as: $\rho=0.6$, $\beta=0.8$, $\alpha=1.0$.

Step 3: Initial weights are taken as $w_{1,1,1}=1, w_{1,2,1}=1, w_{1,3,1}=1$.

Step 4: The first input $NI_{1,1}=0.875$, $NI_{1,2}=1.0$, $NI_{1,3}=0.6667$ is represented to network.

Step 5: For the first failure mode, the choice function value is calculated: $T_{1,1}=0.6354$.

Step 6: The maximum of the calculated choice function values is selected: therefore $T^*=T_{1,1}=0.6354$.

Step 7: Matching test for T^* results in $M_{1,1}=1$, $M_{1,1}>\rho$. First input goes to the first class C_1. Then go to step 9.

Step 9: Updated weights are $w^{new}_{1,1,1}=0.9250$, $w^{new}_{1,1,1}=1.0$, $w^{new}_{1,1,1}=0.8$.

Step 10: Repeat. Go to step 4.

For the second failure mode ($S=5$, $O=6$, $D=6$):

Step 4: Take next input $NI_{2,1}=0.375$, $NI_{2,2}=0.714$, $NI_{2,3}=0.55$.

Step 5: The choice function value is calculated: $T_{2,1}=0.449$.

Step 6: The maximum of the calculated choice function values is selected: therefore $T^*=T_{2,1}=0.449$.

Step 7: Matching test for T^* results in $M_{2,1}=0.76$, $M_{2,1}<\rho$. Then go to step 8.

Step 8: Resetting: Create a new class $s=s+1=2$. This input goes to the new class C_2.

Step 9: Weights are updated: $w_{2,1,1}=0.8005$, $w_{2,2,1}=0.3232$, $w_{2,3,1}=0.6533$ and $w_{2,1,2}=0.3750$, $w_{2,2,2}=0.7143$, $w_{2,3,2}=0.5556$.

Step 10: Repeat. Go to step 4.

For the third failure mode ($S=5$, $O=5$, $D=5$):

Step 4: The next input is $NI_{3,1}=0.375$, $NI_{3,2}=0.5714$, $NI_{3,3}=0.4444$.

Step 5: The choice function values are calculated: $T_{3,1}=0.4115$, $T_{3,2}=0.5729$.

Step 6: The maximum of the calculated choice function values is selected: therefore $T^*=T_{3,2}=0.5729$.

Step 7: Matching test for T^* results in $M_{3,2}=1$, $M_{3,2}>\rho$. This input goes to class C_2. Then go to step 9.

Step 9: Weights are updated: $w_{3,1,1}=0.8005$, $w_{3,2,1}=0.3232$, $w_{3,3,1}=0.6533$ and $w_{3,1,2}=0.3750$, $w_{3,2,2}=0.6286$, $w_{3,3,2}=0.4889$.

Step 10: Repeat. Go to step 4.

The completed Fuzzy ART FMEA algorithm execution results in four classes and their priority is given Table II.

The results of the sample problem solved by both the techniques are analyzed comparatively in Table III.

Table II. Results of classical FMEA and Fuzzy ART FMEA

Failure mode no.	RPN	Results of classical FMEA Class number	Results of Fuzzy ART FMEA Class number
1	504	1	1
27	324	1	1
28	324	1	1
14	270	1	1
4	189	1	1
16	168	1	1
2	180	1	2
3	125	1	2
8	120	1	3
18	120	1	2

Table II. *Continued*

Failure mode no.	RPN	Results of classical FMEA Class number	Results of Fuzzy ART FMEA Class number
22	120	1	3
10	105	1	3
12	105	1	3
21	96	2	4
5	80	2	3
17	80	2	3
19	80	2	3
24	80	2	1
25	80	2	3
6	48	2	4
11	48	2	4
9	40	3	3
23	40	3	3
29	27	3	3
20	27	3	3
7	10	3	3
13	10	3	3
26	9	3	3
15	9	3	3

Table III. The comparison of the findings

Classical FMEA findings	Fuzzy ART FMEA findings
RPN>100: Corrective action required The 13 of the obtained failure modes are greater than 100 and these are defined as surely to have to take precautions. It is obviously seen that this circumstance caused high cost and time loss. In addition, third failure mode $(5\times 5\times 5)$ takes part in this class	*Priority1 class*: Corrective action required The 7 of the obtained failure modes take part in Priority1 class. One has to take precautions urgently. This class' arithmetic mean is 9.857. Twenty-fourth failure mode $(8\times 1\times 10)$ takes part in this class
40<RPN<100: Consider corrective action The 8 of the obtained failure mode take part between 40 and 100. These are the failures that need corrective action. Twenty-fourth failure mode $(8\times 1\times 10)$ takes part in this class	*Priority2 class*: Consider corrective action The 3 of the obtained failure modes take part in Priority2 class. This means corrective action is required. This class' arithmetic mean is 783
RPN ≤ 40: None required The 8 of the obtained failure modes of RPN values are under 40. Therefore there is no need for corrective action	*Priority3 class*: None required The 16 of the obtained failure modes take part in Priority3 class. This means that there is no need for corrective action. This class' arithmetic mean is 4.625 and third failure mode $(5\times 5\times 5)$ takes part in this class.
	Priority4 class: Insignificant The 3 of the obtained failure modes take part in Priority4 class. This means that it is insignificant to take precaution. This class' arithmetic mean is 4.33

DISCUSSION

The aim of this study is to find solutions for the above-mentioned criticism related to classical FMEA methodology. The weak points of the classical methodology stood out in the example that is solved by using

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both classical FMEA and Fuzzy ART FMEA methodology. The proposed Fuzzy ART algorithm in this study makes some significant and remarkable contributions to the weak points of the classical methodology.

One of the important contributions is matching function concept in Fuzzy ART instead of threshold value. In the classical FMEA method, classification needs to determine a threshold value for RPN. This threshold is a clean cut distinct for classes. In the classical FMEA, precautions are taken for all failure modes that are above 100 RPN values. In the proposed algorithm, this matching function determines the classes and their memberships. As a result, failure modes are classified according to their similarity without assigning a threshold.

Corrective precautions are determined for all causes of failure modes above the certain threshold value in the classical FMEA methodology and cost increases with the increase in the number of failure mode. According to the proposed algorithm, it is seen that the number of failures that should be improved decreases and profit gain increases definitely. This fact can be seen obviously in Tables II and III. In the example, the number of failure modes that require corrective action decreases from 13 to 7 through Fuzzy ART algorithm. This is the second important contribution of the algorithm.

The third contribution of the algorithm is about the risk factors' criticality degree. In the classical FMEA method, although three risk factors (severity, detection and occurrence) are assigned separately, the classifications of the failure modes are evaluated by using RPN. Different combinations that have the same RPN value can have dissimiliar criticality. In the classical FMEA method, while severity, occurrence and detection values are totally different from each other, the RPN that is obtained by multiplying these three risk factors can be the same. Because the evaluation is done due to the result of RPN, these values are performed similarly although they are different. However, the risk implication may be totally different as seen from the 5th and 24th failure modes. This situation causes time and source waste or sometimes high risk that is disregarded. For instance, for the fifth failure mode RPN value equals 80 $(8\times 2\times 5)$ in the classical FMEA method and there is no need to take corrective precautions, but in Fuzzy ART methodology, this failure mode is in the Priority4 class. At the same time, for the 24th failure mode RPN value equals $(10, 1, 8)$ 80. Thus, there is no need to take corrective precautions according to the classical FMEA method. However, for Fuzzy ART methodology, this failure mode is in Priority1 class. The classification of failure modes according to the RPN value causes loss of three different risk factor effects.

In the proposed Fuzzy ART method, severity (S), detection (D) and occurrence (O) values are evaluated separately for each input. Thus, inputs with lower RPN can be classified into higher priority class or vice versa. For instance, for the third failure mode, the RPN value equals 125 $(5\times 5\times 5)$ in the classical FMEA method proposed corrective precautions, but in Fuzzy ART methodology, this failure mode is in the Priority2 class. For the 24th failure mode, the RPN value $(10, 1, 8)$ is 80. Therefore, there is no need to take corrective precautions with respect to the classical FMEA method. Although severity and detection values are at a very high level and need corrective precautions urgently, the RPN value that is obtained from the multiplication of three risk factors is equal to 80, the failure mode prioritization is ignored. But in Fuzzy ART methodology, this failure mode is in Priority1 class. This is the fourth contribution of the algorithm.

Another shortcoming of the RPN is that some numbers between 1 and 1000 cannot be obtained from the three risk factors, for example, $11, 22, 33, \ldots, 990$. Briefly, in the classical FMEA method, a maximum of 120 RPN values can be generated from $(10\times 10\times 10)$ 1000 different RPN combinations. In Fuzzy ART FMEA method, severity, occurrence and detection values composing RPN are considered separately; therefore, all of RPN values between $\{1, 2, 3, \ldots, 1000\}$ are obtainable. This is the fifth significant contribution of the algorithm.

CONCLUSION

While the classical FMEA method covers an important requirement, it is well known that it has several shortcomings. Therefore, in this study, Fuzzy ART neural network is applied to FMEA and successful results are acquired.

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The following targets are reached by applying the developed methodology:

- Doing the evaluations of failure modes with a more mathematical-based method.
- Approach should be used to find solutions to the points at which the classical FMEA method fails.
- The process of prioritization of failure modes should be kept separate from the sensitivity of participants' experience level.
- Method can be applied simply and easily.

However, RPN computation method in the classical FMEA method has become subjective because the grading rules of severity, probability and detection criteria could be changed with respect to participants' information level and experience. In addition, in some cases, the solution cost could be higher than the cause cost but this situation could not be reflected in the determination of priorities. The cost of defect type has been set off as precautions for solutions.

A solution for the two criticisms addressed above could not be provided in this study. This case will be the subject of future work.

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