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# Using Artificial Neural Network and Fuzzy Inference System Based Prediction to Improve Failure Mode and Effects Analysis: A Case Study of the Busbars Production

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**Abstract:** Nowadays, Busbars have been extensively used in electrical vehicle industry. Therefore, improving the risk assessment for the production could help to screen the associated failure and take necessary actions to minimize the risk. In this research, a fuzzy inference system (FIS) and artificial neural network (ANN) were used to avoid the shortcomings of the classical method by creating new models for risk assessment with higher accuracy. A dataset includes 58 samples are used to create the models. Mamdani fuzzy model and ANN model were developed using MATLAB software. The results showed that the proposed models give a higher level of accuracy compared to the classical method. Furthermore, a fuzzy model reveals that it is more precise and reliable than the ANN and classical models, especially in case of decision making.

**Keywords:** fuzzy inference system (FIS); artificial neural network (ANN); failure mode and effects analysis (FMEA); risk priority number (RPN); busbars; Industry 4.0



**Citation:** Na'amnh, S.; Salim, M.B.; Husti, I.; Daróczi, M. Using Artificial Neural Network and Fuzzy Inference System Based Prediction to Improve Failure Mode and Effects Analysis: A Case Study of the Busbars Production. *Processes* **2021**, *9*, 1444. https://doi.org/10.3390/pr9081444

Academic Editor: Wen-Jer Chang

Received: 26 July 2021
Accepted: 17 August 2021
Published: 19 August 2021



## 1. Introduction

As the world's economy is developing rapidly, many companies started focusing their efforts on innovation technology so that they can obtain competitive privilege in the future. Furthermore, these innovations aim to mitigate the development cycle of products and provide customers distinguished products at high quality and low cost [1]. However, achieving these requirements is still a challenge for many organizations [2]. Recently, several methods have been used to develop the quality of service and products by minimizing or eliminating potential errors or failures. One of the popular methods is the failure modes and effects analysis (FMEA), which is considered an efficient method and is vastly used in the process of service and production [3,4].

Failure modes and effects analysis (FMEA) is an analytical tool for detecting, defining, and lessening the potential failures that may occur for the product and process systematically by identifying the root causes, potential occurrence, and consequences [5]. FMEA provides a numeric score to compute the failures where each failure is converted to a number to evaluate the value of the risk priority number (RPN). RPN is the final result after multiplication of the three parameters: Severity (S), Occurrence (O), and Detectability (D). Severity, in this study, represents the risk of damage that may take place during the manufacturing process of the busbar part, while the occurrence is the failure likelihood to happen again. Finally, detectability is the degree to which this failure could be detected [6,7]. A higher RPN value means a higher priority of risk [8].

In 1963, NASA improved the FMEA to promote the effectiveness of the tools that are used in the aerospace industry [9]. Ford Motors had developed and adopted the FMEA in 1977 [10]. At the moment, FMEA is commonly being used in the automotive industry to enhance the reliability and quality of production process, and it is used to make sure that all failure modes have been taken into account and assessed duly to mitigate, or even eliminate, the failure [11]. FMEA is divided into two types: the design FMEA and the process FMEA. Design FMEA detects the weakness of product design; whereas process FMEA concentrates on the potential problems of the planning process [10]. However, many researchers demonstrated that the conventional FMEA also has some weaknesses [12]. These weaknesses can be divided into two parts: the evaluation method of the risk factors and the risk priority number (RPN) calculation. First, FMEA documents are obtained by engineers and experts using linguistic idioms that depend on the personal evaluation and experts' knowledge, therefore, removing the impact of subjectivity and judgment of man-made evaluation becomes a crucial concern [13]. Second, RPN is also doubted because of its shortcomings [14] which are mentioned below:

1. The three risk factors are assumed to be equally weighted, and the importance of each factor is considered, which makes the results in the risk assessment process inaccurate because this may not be the case when considering a practical application of FMEA [15].
2. The RPN elements have many duplicate numbers because the multiplication of S, O, and D can produce the same value of RPNs, while the risk potential may be totally different.
3. The judgment on risk factors from different experts to get single values of S, O, and D may lead to loss of valuable information.
4. The mathematical formula for calculating RPN is doubtful and highly sensitive to variations in risk factor evaluations. Small variations in one rating make a high different effect on the RPN.

Chang et al. in [10] have criticized the RPN calculation method by the incommensurate correlations among the three parameters. His criticism is according to the fact that these three parameters are linearly multiplied together with a similar scale. This process is carried out without any consideration of the actual impact of each independent parameter and the different qualitative meaning of the scale. For example, high severity value means a high RPN value due to the serious hazard on the operator or the machine. Hence, if there is a risk on humans, the other parameters shouldn't decline the overall value of the risk priority number (RPN) even if they are low.

Therefore, in order to avert this vagueness, researchers suggested many methods to enhance the application of FMEA and the improvement of RPN. Many fuzzy approaches were suggested to improve a new risk assessment approach to overcome the weaknesses and fragility of classical FMEA. For example, to improve the ambiguity and uncertainty in the evaluation of risk factors, Zhang and Chu [16] proposed a new method by integrating fuzzy RPNs by using a weighted least square method. This is an imprecision and partial ranking technique that can acquire more accurate fuzzy RPNs and improve the reliability of the evaluation process under uncertainty. Zhou et al. [17] considered the problems of unavoidable bias of expert assessment and the difficulty of determining the evaluation weights; thus, they offered an improved FMEA method that depends on the linguistic weighted geometric (LWG) operator and fuzzy priority. The meaning of LWG can avoid information loss in the evaluation process. Meanwhile, the fuzzy priority was used to calculate the evaluation weights based on the consistency of experts. This approach can provide a lower weight for the evaluation, which has low consistency and reduces its impacts on the results. Rabbi [18] showed that difficulties such as ambiguous information and opinion differences among the experts can reduce the validity of the results in conventional FMEA. Thus, he used a fuzzy logic FMEA method based on fuzzy IF-THEN rules to make it more accurate comparing with the classical one.

Considering the problems of the RPN calculation process, Haktanır and Kahraman [19] have presented many fuzzy methods and grey theory. They suggested interval-valued neutrosophic (IVN) sets-based FMEA to remove the inaccuracy and subjectivity of the human decisions. Ayber and Erginel in [20] have used single-valued neutrosophic (SVN)

Fuzzy FMEA as a new risk analysis method to avoid the ambiguity of the linguistic idioms. Al-Khafaji et al. in [21] have suggested a fuzzy multicriteria decision-making model consistent with FMEA principles to get a reliable method for maintenance management. Liu et al. in [8] have presented the cloud model theory and hierarchical TOPSIS approach to improve FMEA performance, avoiding potential bias of human judgment, and simplifying the change of qualitative terms to quantitative values. Yang et al. in [6] have used a data mining-based approach for isolating faults, depending on FMEA parameters, to improve predictive maintenance by using historical big data to make data-driven models, by which future failure can be predicted properly and subsequently avert failures at a very critical operational item. Keskin and Özkan in [22] have utilized a fuzzy adaptive resonance theory (ART) method for FMEA modeling to enhance the conventional method of calculating the RPN, which, in total, reduced cost and efforts required to react with corrective actions alerts.

The above-mentioned research reveals that proper works have been established to enhance the FMEA method work well in specific applications. However, the weakness of FMEA and RPN is not limited to the ambiguity of the FMEA quantitative description or its textual representation, but it also extends to the necessity of being a proactive tool with high responsiveness to failures. Another drawback of the conventional FMEA technique comes from the fact that its documents are produced during the product or process design stages, which makes these documents outdated after production starts. Therefore, these documents are required to be continuously updated and validated. Adopting new methods is very important to avert these shortcomings and keep these documents responsive [6].

At the time of Industry 4.0, communication and cooperation have become easier than before. Machine learning (ML), Artificial intelligence (AI), Cyber-physical systems (CPS), Internet of things (IoT), and big data made a remarkable evolution in manufacturing automation. Here, automation is no longer exclusive only for machines and processes but also for management aspects such as enterprise resources planning (ERP), customer relationship management (CRM), and quality management systems (QMS) [23]. Moreover, the real-time flow of data among the value chain, which is analyzed and transformed into user-friendly information (special thanks here to the advanced supercomputing and analyzing power [24]) resulted in new models of manufacturing systems, which are being known nowadays by smart factory, smart machine, smart product, and augmented operator [25]. These technologies converted the concepts of production systems from being reactive to being proactive and boost the human interference from doing the work to supervising it while it is being done. Sensors, 3D cameras, radio frequency identifier (RFID), and Wi-Fi made monitoring processes more accurate. Invisible defects or deviation of products and processes can be instantly discovered at the time of occurring. Defect elimination and processes modification are made autonomously at the micro and macro levels [23]. All these technologies, besides the increasing in complexity of products and their manufacturing systems, delivered a huge volume of data at a high veracity and remarkable speed. Analyzing big data needs sophisticated techniques to distribute data that cannot be detected by using traditional analytical methods.

Artificial neural network is a very beneficial method in solving several medical, engineering, and mathematical problems. The concept of artificial neural network was presented around the 1950s to imitate the different activities of the human brain. An artificial neural network works as a parallel distributed information processor made up of identical units (neurons) capable of saving information and making it obtainable for use. Mathematically, ANN is a type of interpolation technique where we have a set of input data and their corresponding functional value [26].

Many applications of artificial neural network function in real life, such as speech recognition, handwriting recognition, etc. The main purpose of neural network is to solve many problems in the same way that a human brain does. The first computational model of ANN has been presented by McCulloh and Pitts [27] in 1943, which shows the concept of a neuron that receives inputs and then process those inputs to give an output the same as the biological neuron, which receives information, processes it, and transfers information to some other neuron by electrical or chemical signals. As such, in the case of ANN, the synapse signals are real numbers that represent the weight of the network, and the output can be computed after passing through a nonlinear activation function. Basically, the ANN contains three layers, namely the input layer, hidden layer, and output layer. It's also possible for there to be more than one hidden layer in between the input and output layer.

This paper proposed a solution to attain consistency in risk evaluation by using machine learning techniques to analyze failures Figure 1 illustrates the research framework in the proposed approach. Machine learning techniques offer the ability to analyze the data as inputs and outputs. This serves in finding and analyzing unseen parameters. Additionally, exploiting this new technology is very important in the industry because of its features in analyzing that exceed human ability. Moreover, this study offers a reliable decision-making tool to enhance the risk assessment. Sami [28] suggested Google AutoML to improve the Risk assessment, but the vagueness and uncertainty still exist. Subsequently, making the decision and defining the risk priority will be affected, and the results are not precise enough.

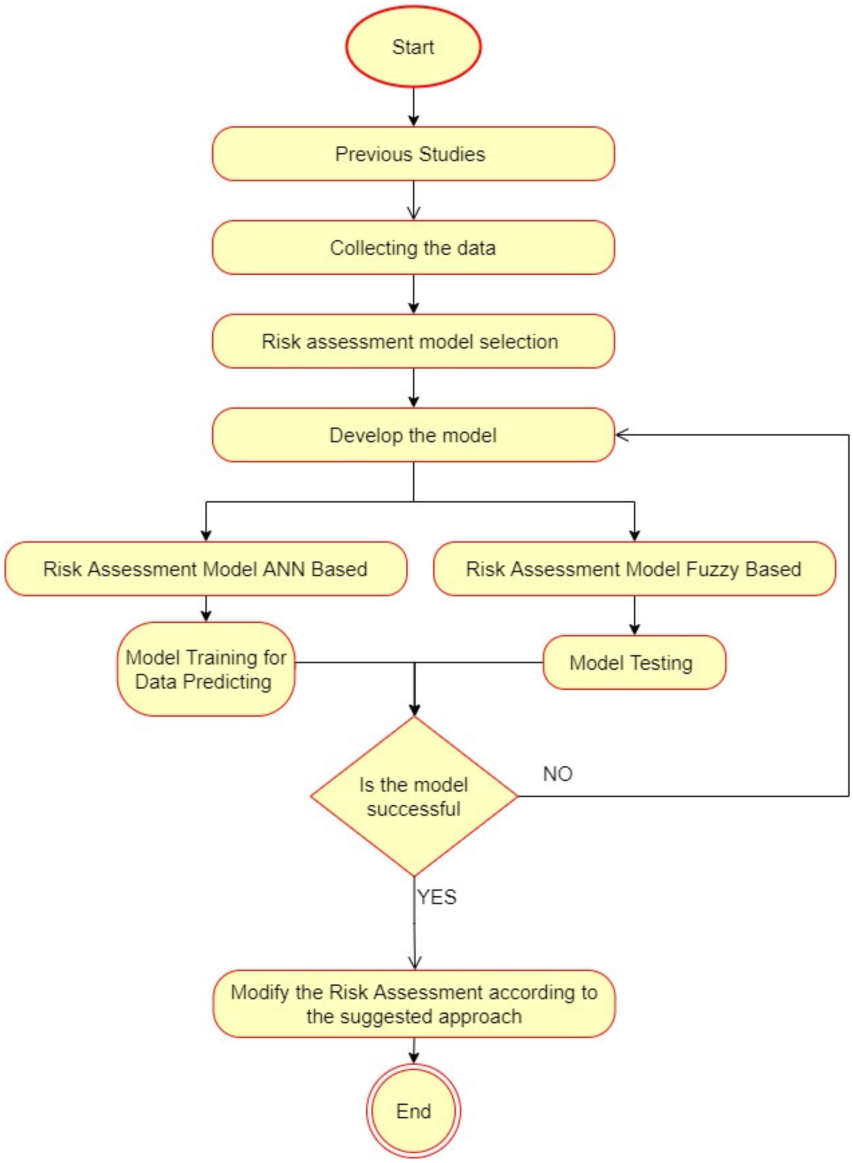



**Figure 1.** Research Framework.

## 2. Study Background

In this research, Nematech Kft is adapted as a case study. Nematech was established in 1993 in Hungary as a subsidiary company of Froeteck GmBH Group. Froeteck group is an international German family-owned business company based in Germany and owns many manufacturing plants worldwide. Nematech/Froeteck is a world-leading manufacturer of electrical connectors, especially the busbars for the automotive industry. It offers all products for the assembly of industrial batteries from individual battery cells. Busbar has been spread widely and used in several areas, such as, aviation industry, automotive industry, ships, illumination industry and electronic devices for military. Currently, the busbar has already been a significant part of electrical vehicles such as forklifts and electrical cars since these vehicles are mainly using the busbars as a typical component of their batteries. Nematech manufactures the busbars, and these busbars are shipped from Hungary to the mother company, that is located in Germany, and directly to the end-customers for final assembly with the machine, which can be a battery pack system for electrical vehicles, as shown in (Figure 2). The cost of a single failure is tremendously high, not only because of the product cost itself but also because of the entailed logistics and the re-work cost. To produce Busbars, many steps should be implemented to acquire the final product, and these steps depend on the usage of the product. For example, to produce aluminum Busbar ground connections (Figure 3), the following processes in (Figure 4) should be implemented:

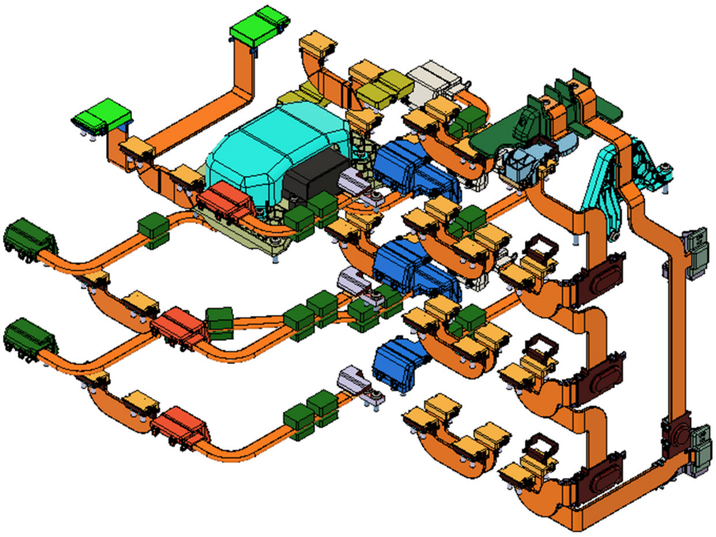


**Figure 2.** Assembled Busbars to compose the battery pack system.

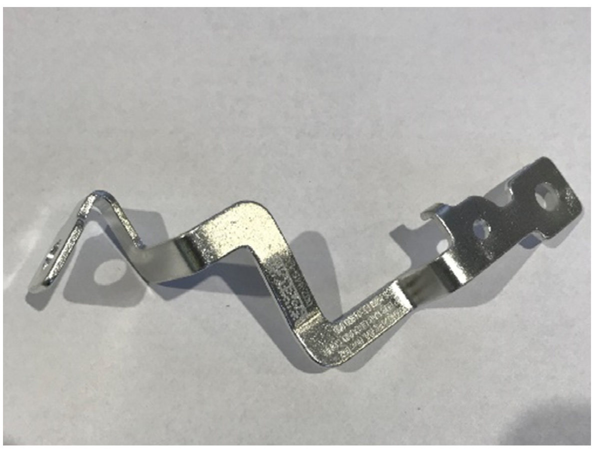


**Figure 3.** Aluminum (EN AW 5005A-H24) Busbar ground connection galvanized by (Cu: 3 +3/0) µm. (Sn: 7 +4/0) µm.

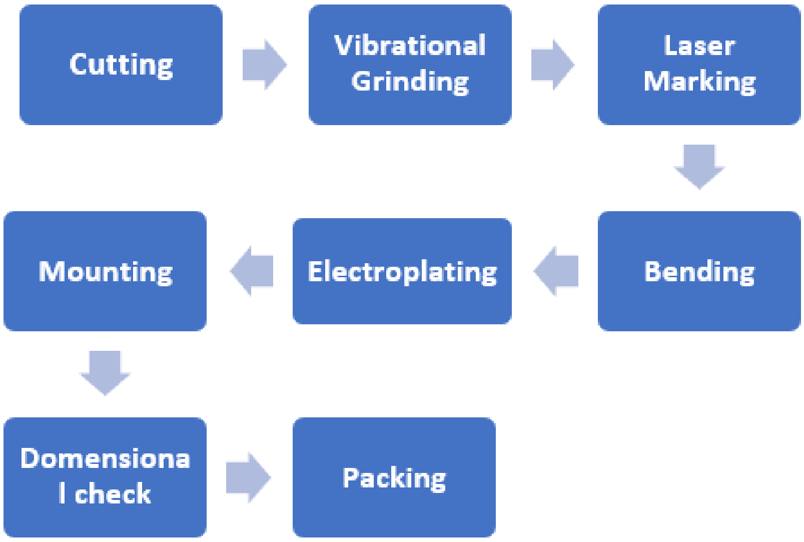



**Figure 4.** Process flow to produce aluminum Busbar ground connection.

The staff has prepared "Quality Checklists" for every product and process. These quality checklists are made according to the FMEA documents and are being used in the production line in order to emphasize that common failure causes are averted. However, as mentioned previously, FMEA documents are developed during the product design and can be modified or changed once the serial production is started. Meanwhile, further failure modes can be exposed at the final assembly stage. Therefore, these quality checklists are needed to be updatable and responsive to the issues reported during or after production.

The company uses conventional FMEA technique by obtaining RPN for each failure, according to FMEA documents. RPN, in this case, is obtained by multiplying three major parameters together (severity, occurrence, and detection) according to Equation (1). The weight of each parameter ranges from 1 to 10.

$$\text{RPN} = \text{Severity} \times \text{Occurrence} \times \text{Detection} \quad (1)$$

Making evaluation and ranking for the process demands well-experienced people who understand the FMEA functions and its purposes. The volume, velocity, and veracity of failure reported and their processing time is extremely important for the quality management. It is vital, in this industry, to detect and solve issues at the moment of occurrence. Moreover, standardizing the evaluation and ranking approach of the process is important to keep the consistency in RPN values every time.

## 3. Methodology

This research was carried out by implementing two machine learning models FIS and ANN. The experts from the quality department prepared the conventional risk assessment for the busbar production by specifying and quantifying each factor (Occurrence, Severity, Detection). Afterward, by fuzzifying each factor, RPN values were calculated. Based on the main identified factors artificial neural networks (ANNs) have been used, a risk assessment model of the busbar production was implemented by Matlab-R2019a software. In this model, at least 58 data were used in the ANN model. Finally, to validate the suggested model, the results and outputs of both risk assessment models, based on a FIS and ANN, were compared with the experts' risk assessment

### *3.1. Fuzzy Interference System (FIS) Risk Assessment Model*

FIS is a popular computational method based on the concepts of fuzzy set theory, fuzzy "if-then" rules, and fuzzy logic. In this research, the Mamdani method was adopted to create a fuzzy inference system (FIS) risk assessment as shown in Figure 5a. The purpose for using this model because the output values are fuzzy sets also widely used for capturing expert knowledge. Moreover, it is ideal to characterize the expertise intuitively and with a more humanlike mode, whereas in other methods, such as the Sugeno fuzzy model and the Tsukamoto FIS, the output values are constant or linear. For defuzzification, the center of gravity (CoG) was implemented. The benefit of this method is that all active rules in the results are incorporated into the defuzzification process [29]. Mathematically, this center of gravity (COG) is given in Equation (4). Since the fuzzy logic method depends on "if-then" rules, the opinions of experts were considered to define the rules. Overall, 58 failure modes (FM) were identified and weighted as shown in Figure 5. Based on the determined parameters in the Matlab fuzzy toolbox, a relation between each parameter was identified as "if-then" rules from type "and". Based on this classification, occurrence, severity, and detection values are classified into five levels (Almost none, Low, Medium, High, and Very high), Overall, 125 fuzzy rules were generated. While the output FRPN is classified into ten levels (None, Very low, Low, High low, Low medium, Medium, High medium, Low high, High, Very high). As a membership function, triangle membership function (trimf) was used to perform the input parameter (O, S, D) Equation (2), whereas Gaussian membership (gaussmf) function was used for output (RPN) in this study Equation (3).

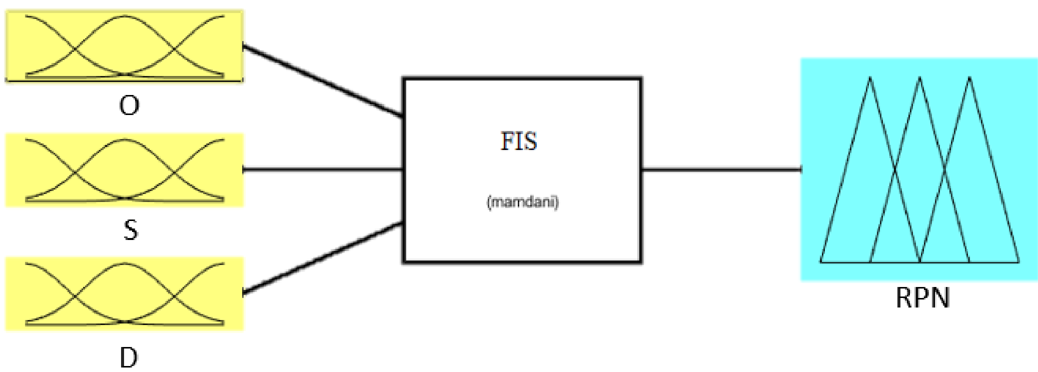
$$f(x;a;b;c) = \left\{ \begin{array}{c} 0 \quad , x \le a \\ \frac{x-a}{b-a} \, , \, a \le x \le b \\ \frac{c-x}{c-b} \, , \, b \le x \le c \end{array} \right\} \tag{2}$$

$$f(x;\sigma;c)exp = \left( \frac{-(x-c)^2}{2\sigma^2} \right) \tag{3}$$

σ: standard deviation, c: mean.

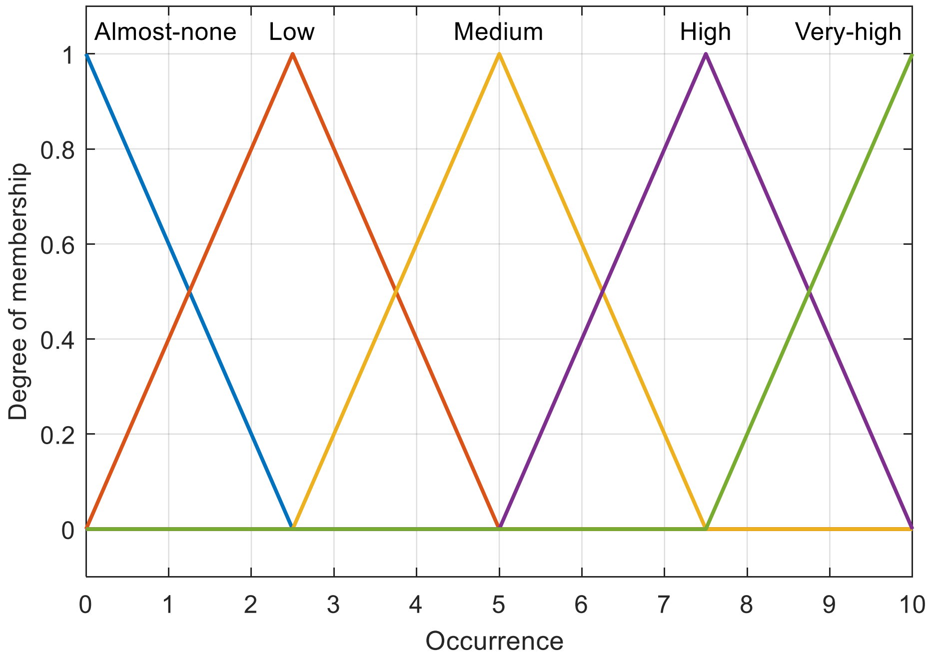
$$COG = \frac{\int_a^b \mu_A\,(X)x.dx}{\int_a^b \mu_A\,(X)x.dx} \tag{4}$$

where $\mu_A\,(X)$ represents the degree of membership of element $x$ in fuzzy set A for each $x \in X$. Centroid defuzzification method finds a point representing the center of gravity of the fuzzy set, A, on the interval, ab.

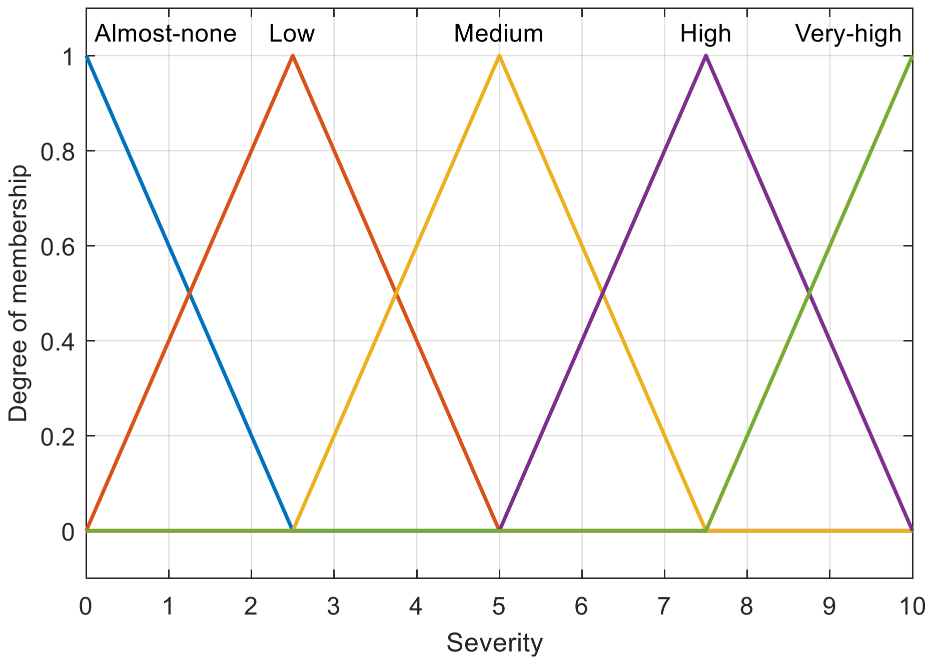



(a)

**Figure 5.** *Cont.*

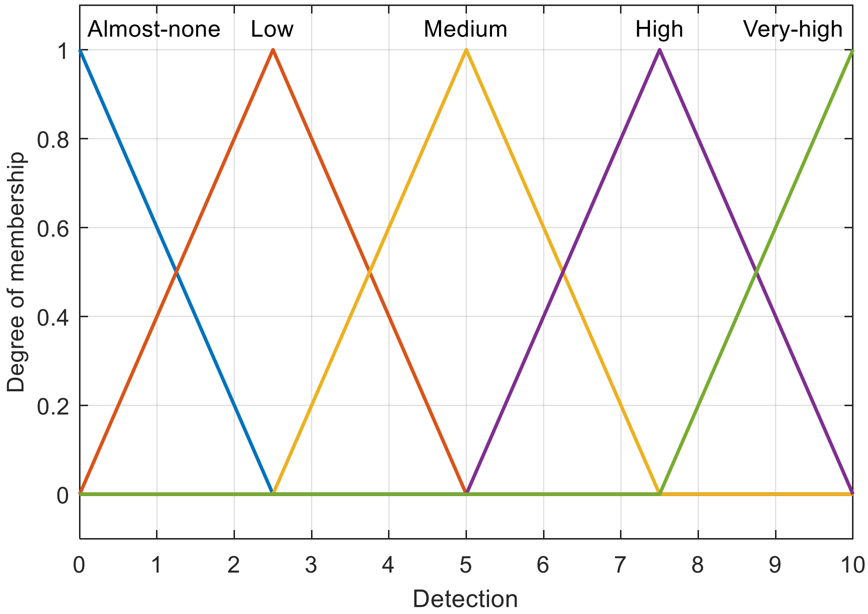



(**b**)

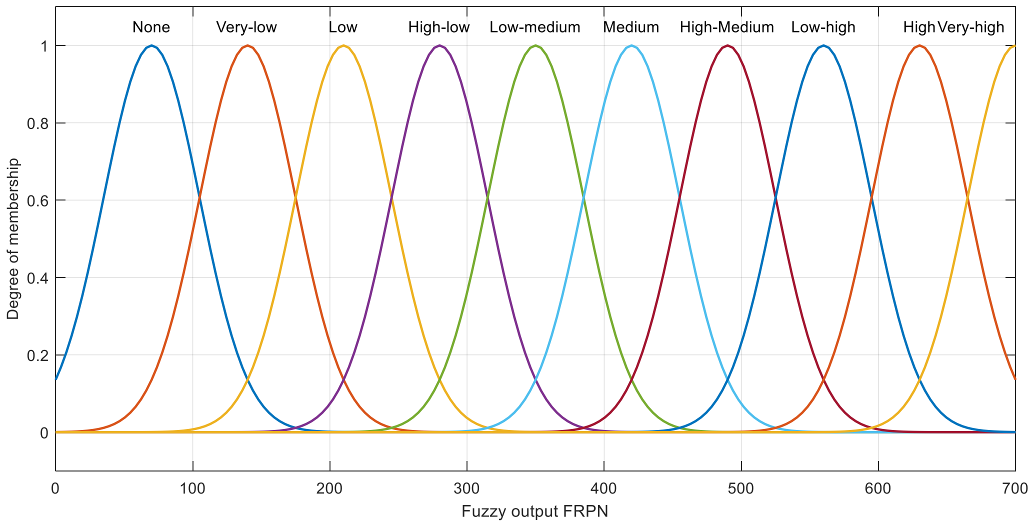



(**c**)

**Figure 5.** *Cont.*




(**d**)




(**e**)

**Figure 5.** Fuzzy set diagram. (**a**) Structure of the design system, (**b**) Occurrence, (**c**) Severity, (**d**) Detection, (**e**) Fuzzy output FRPN.

### *3.2. Artificial Neural Network (ANN) Risk Assessment Model*

The suggested risk assessment model was based on a neural network model (ANN). The model was made by MATLAB Neural Network algorithm. The model was created with three important factors affecting the busbar production risk, which are the most relevant elements to compose the FMEA. In this study, the acquired data from inspection and failure reports were reanalyzed in accordance with the predefined variables. Consequently, they were prepared and quantified to enter the networks. Finally, based on the best performance of the ANN model and the limitation of the dataset, 90% of data were selected as training data, 10% as validation data. The data were selected randomly in MATLAB 2019. Concerning the target of current research, many types of ANNs might be suitable for the current study. Among all, Multi-Layer Perceptron (MLP) was selected, which is commonly used as ANN structure. Due to the nature of FMEA, Feed forward ANN was implemented as the suitable and effective choice for risk modeling. Based on the trial-and-error approach, it was found that the ANN was appropriate for our study. Input layers, hidden layers, output layers, and other parameters are defined in Table 1 and Figure 6.

**Table 1.** Selected parameters of the suggested ANN model.

| Model Parameter | ANN |
|---|---|
| Number of layers | 3 |
| Number of neurons in hidden layer 1 | 50 |
| Number of neurons hidden layer 2 | 30 |
| Number of neurons in the output layer | 1 |
| Size of all of dataset | 58 |
| Size of training dataset | 90% |
| Size of validation dataset | 10% |
| Number of epochs | 1000 |
| Training function | trainlim |
| Transfer function for hidden layer 1 | tansig |
| Transfer function for hidden layer 2 | tansig |
| Transfer function output layer | purelin |

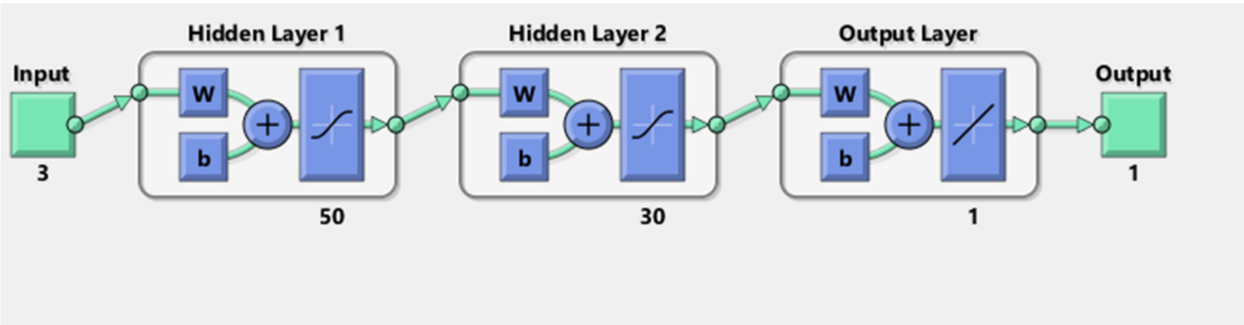



**Figure 6.** The architecture of the selected ANN.

To perform the model performance and finding the suitable network structure, the correlation coefficient (R), which measures the accuracy of the model to predict the outputs and the root mean squared error (MSE), was used, which represents the error of the predicted results. Obtaining low MSE and high R means that the developed network is optimal. To attain the best integration of transfer functions in the network, various types of transfer functions in hidden layers were used to create the network. As shown in Table 1, the best integration of transfer functions by using Tansig functions for the input layers and Purelin functions for the output layers, while the Trainlm function was implemented for the training layer.

It is important to determine the number of hidden layers to develop a network with the low error value in predicted outputs. Trial and error procedures are generally used to obtain the optimal number of hidden layers; therefore, a model with the minimum number of hidden layers means less time to train the network, but it does not mean that the results will always be acceptable. In this case, increasing the number of hidden layers and the number of neurons may achieve better results even if the training time is longer.

## 4. Results and Discussion

Firstly, the classical FMEA was developed to determine the main three parameters occurrence (O), severity (S), and detectability (D) which are shown in Table A1. The RPN was evaluated for each failure based on these parameters. The values for the occurrence, severity, and detectability were estimated by the quality staff according to the experience acquired. After the RPN values are determined, a decision is taken by considering severity, detectability, and occurrence, respectively, to rank the parameters. Fuzzy logic was also implemented in order to avoid the shortcoming in conventional FMEA. The fuzzy memberships values for input and output are provided in Tables 2 and 3 and shown in Figure 5a–e.

**Table 2.** Linguistic terms of fuzzy memberships—inputs (Occurrence (O), Severity (O), Detection (D)).

| Linguistic Terms | Fuzzy Membership Numbers |
|---|---|
| Almost None | (0,0,2.5) |
| Low | (0,2.5,5) |
| Medium | (2.5,5,7.5) |
| High | (5,7.5,10) |
| Very High | (7.5,10,10) |

**Table 3.** Linguistic terms of fuzzy memberships—output (RPN).

| Linguistic Terms | Fuzzy Membership Numbers |
|---|---|
| Almost None | (35,70) |
| Very low | (35,140) |
| Low | (35,210) |
| High low | (35,280) |
| Low medium | (35,350) |
| Medium | (35,420) |
| High medium | (35,490) |
| Low high | (35,560) |
| High | (35,630) |
| Very high | (35,700) |

The relationship between occurrence, severity, detection, and FRPN can be presented by three-dimensional plot that performs the mapping from two inputs (occurrence, severity, or detection) to one output (FRPN), as shown in Figure 7. In the case of the fuzzy logic method and the classical method, it is obvious that the fuzzy provides a wider range of risk assessment and smaller intervals between different levels of risk, which means higher accuracy could be achieved.

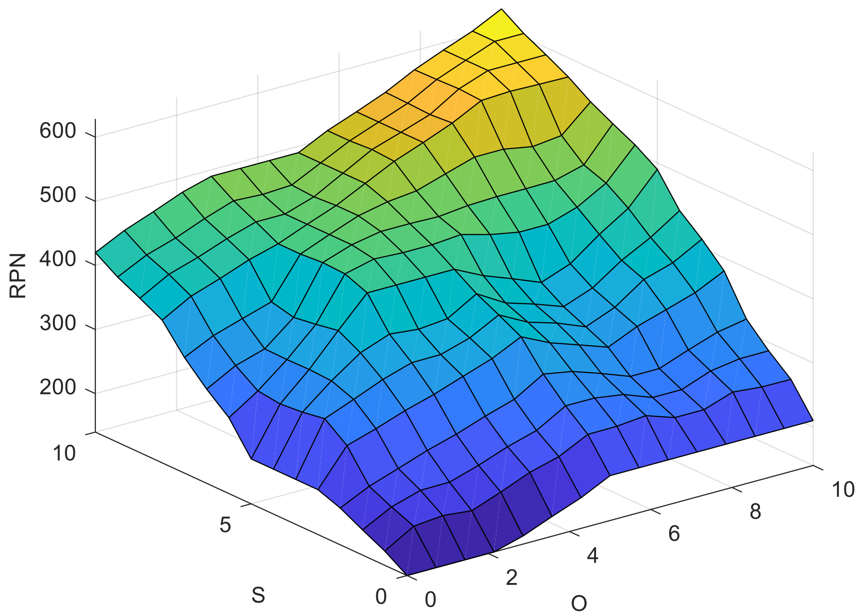



**Figure 7.** Three-dimensional plot between two inputs (S, O) and fuzzy-RPN output.

As can be seen, the obtained results from the fuzzy model are much more realistic than the classical one. The classical model considers the human judgment in decision making, unlike the fuzzy model, where the human subjectivity is eliminated and according to that, the risk priority for each failure mode has been changed, and Table A2 confirms that. For example:

The value of Classical RPNFM1 = 560 which is the multiplication of three parameters (O = 7, S = 8, D = 10) and the value of FRPNFM1 = 651.56.
The value of Classical RPNFM52 = 648 which is the multiplication of three parameters (O = 9, S = 9, D = 8) and the value of FRPNFM52 = 639.2.
The value of Classical RPNFM15 = 400 which is the multiplication of three parameters (O = 5, S = 10, D = 8) and the value of FRPNFM15 = 628.3.
The value of RPNFM58 = 448 which is the multiplication of three parameters (O = 7, S = 8, D = 8) and the value of FRPNFM58 = 612.

Based on the classical FMEA, the FM58 is prior to FM1. The classical model missed the importance of high value of detection in FM1, which drives the wrong priority evaluation and thus wrong decision making. However, the fuzzy model has overcome this problem and developed the correct assessment by taking the detection high value in the consideration and changed the priority of the FM1 from priority 2 to 1. Although the values of other parameters O and S are high for FM52, FM1 is still riskier, and the same situation applies for FM15 and FM58. The classical FMEA did not provide a correct weight for severity, but the fuzzy model provided the correct weight for severity parameter, and that is why FM15 is prior to FM58. The RPN behavior, with failure mode for the classical method and fuzzy method, is demonstrated in Figure 8. It's obvious that FRPN behaves the same as actual RPN with some deviations. This deviation cannot be considered an error, but it is coming from the scale difference between two models.

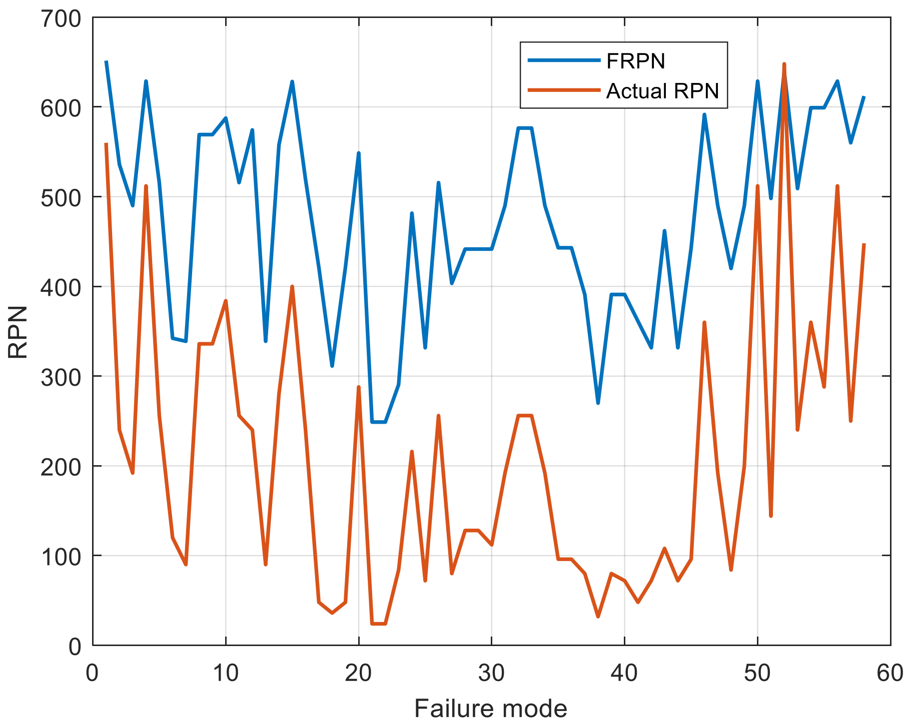



**Figure 8.** RPN representation in both models, Actual vs. Fuzzy.

To acquire a more accurate model, the ANN model was trained to create a proper relationship between inputs and outputs to have valid outputs. ANN has been used to learn the risk assessment mapping functions. The ability of ANN was improved by carefully choosing the number of neurons in the hidden layers. The number of neurons in the hidden layers will have a critical impact on the performance of the ANN. Figure 9 shows the best training performance data of the suggested network. The data used for training were 52 and 6 for validation. In order to predict the value of RPN, the correlation coefficient R is

0.99, which is shown in Figure 10, and the MSE is $4.6636 \times 10^{-8}$, representing the accuracy of the model in predicting the outputs.

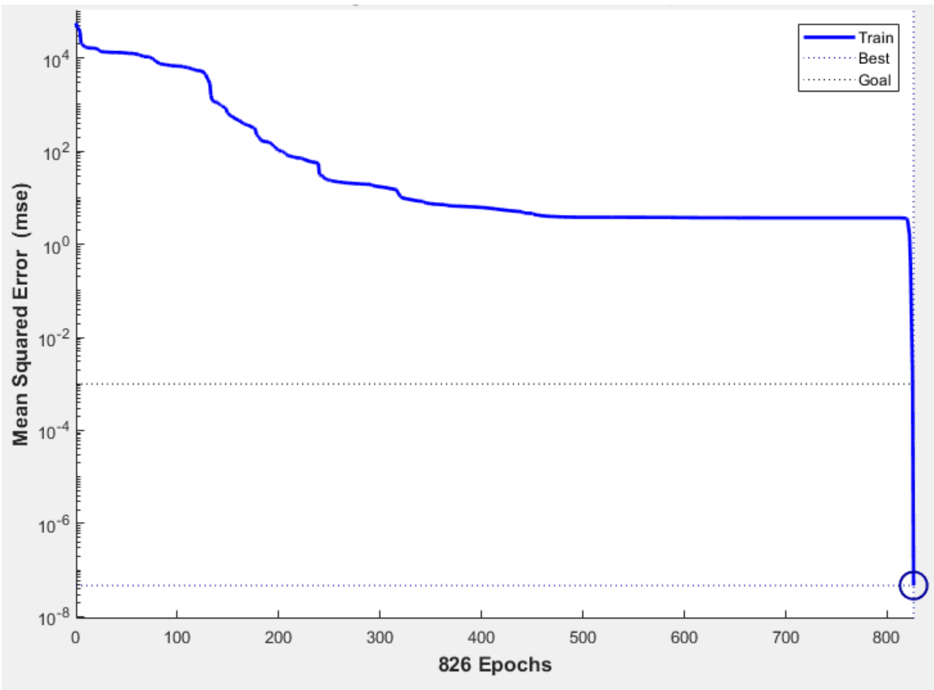



**Figure 9.** Best Training Performance is $4.6636 \times 10^{-8}$ at epoch 826 for the suggested network.

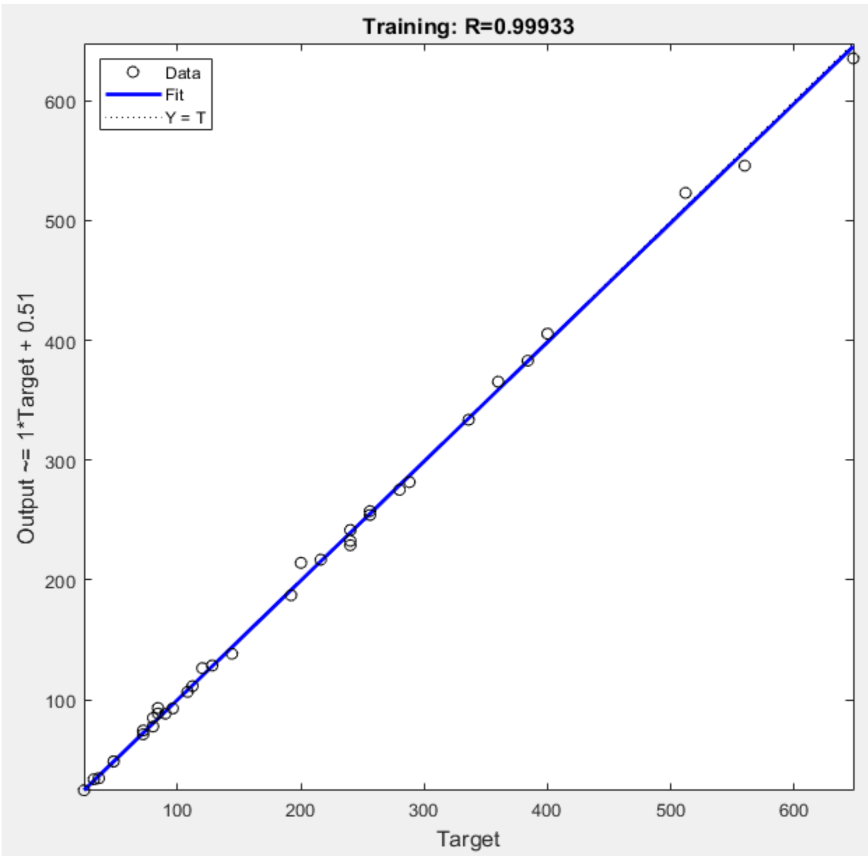



**Figure 10.** ANN model correlation coefficient value for outputs based on actual data for Training.

After training, Figure 11 shows very good prediction, and both results are almost close together. The output results are listed in Table A1. The results revealed that using ANN is a very promising method for prediction and proved their efficiency to simulate the risk assessment, and based on that, some Failure mode priorities have been changed. For example:

The value of Classical $RPN_{FM2}$ = 240 which is the multiplication of three parameters (O = 5, S = 8, D = 6) and the value of $FRPN_{FM2}$ = 535.92 and ANN_ $RPN_{FM2}$ = 232.62
The value of Classical $RPN_{FM12}$ = 240 which is the multiplication of three parameters (O = 3, S = 8, D = 10) and the value of $FRPN_{FM12}$ = 574.37 and ANN_ $RPN_{FM12}$ = 241.7
The value of Classical $RPN_{FM16}$ = 240 which is the multiplication of three parameters (O = 6, S = 8, D = 5) and the value of $FRPN_{FM16}$ = 519.05 and ANN_ $RPN_{FM16}$ = 228.91

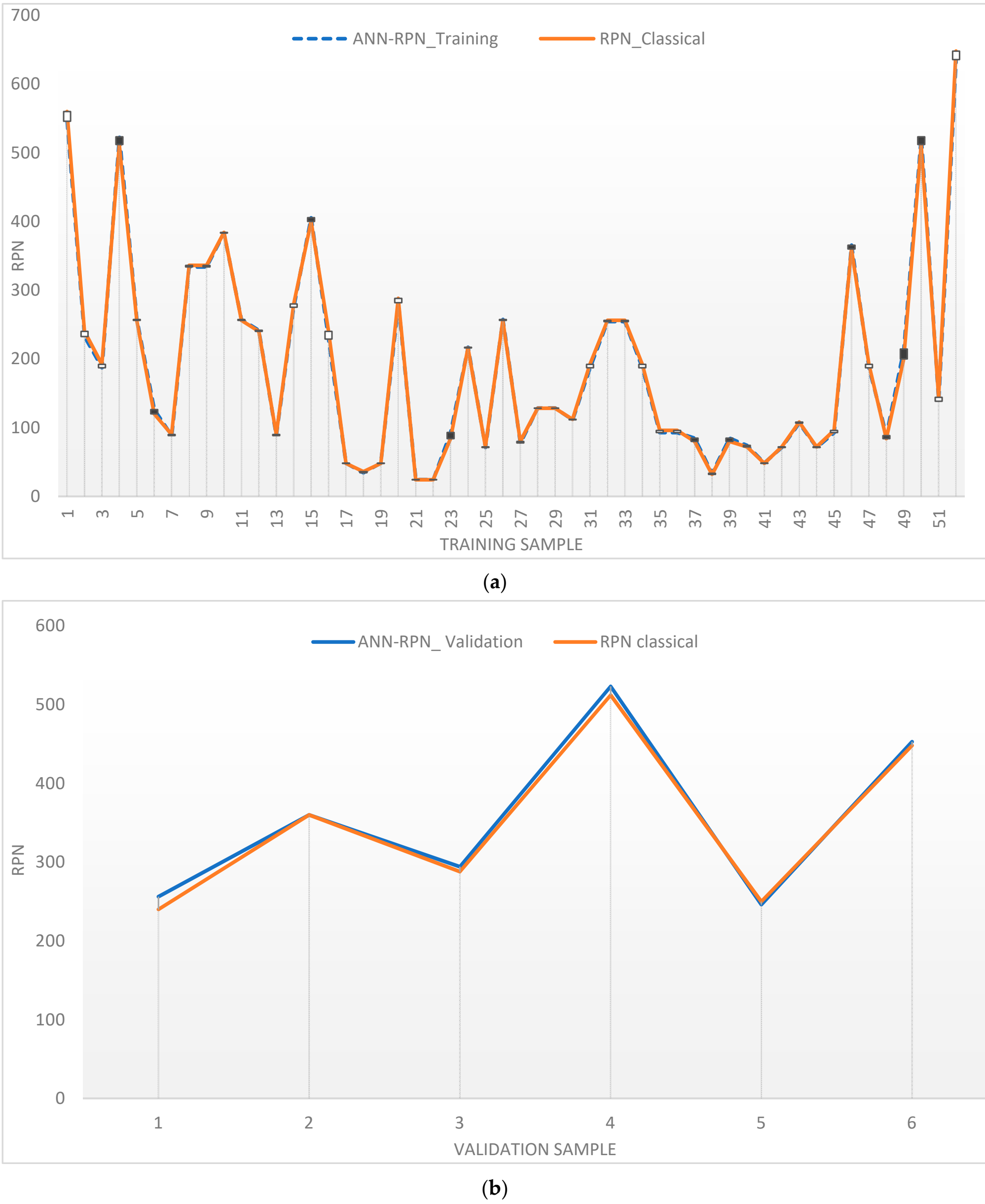



**Figure 11.** Demonstrating the prediction of ANN-RPN for training samples and validation samples. (**a**) ANN-RPN_Training and RPN_Classical vs. Training sample, (**b**) ANN-RPN_Validation and RPN_Classical vs. Validation sample.

The Classical FMEA provide duplicate RPN values for FM2, FM12, and FM16, despite of different values for occurrence, severity, and detection without considering the importance of the parameter. However, the ANN model and Fuzzy model have averted this inconvenience in results and have provided a consistent result by considering the importance and the weights of the three parameters. Since the value of severity is the same in the three failure modes, both models considered the importance of occurrence and detection, and thus, FM12 is prior to FM2 because D = 10, and FM2 prior to FM16 D = 6, although the occurrence value in FM16 is higher than in FM2, but the weight of detection has more effects on the risk assessment in this case.

However, the ANN model has some prediction errors which have been noticed, such as predicting the value of RPN for FM23 and FM35, where the FM35 should be prior to FM23 based on the (O, S, D) values. The error happened between FM17 and FM41. FM41 should be prior to FM17 and also between FM7 and FM48. FM48 should be prior to FM7. The explanation for this error belongs to the limited dataset, and by increasing the training and the validation samples mapping, the data will be improved as well as the model ability for learning. Interesting enough to be mentioned, the fuzzy method has not recorded the same error in prediction the output, unlike the ANN. All output values were consistent, reliable, and worthy to be used to create the FMEA. Furthermore, fuzzy method was the best for risk assessment prediction among the others, which means it's the superior choice for decision-making applications, and Figure 12 shows the RPN values based on three methods.

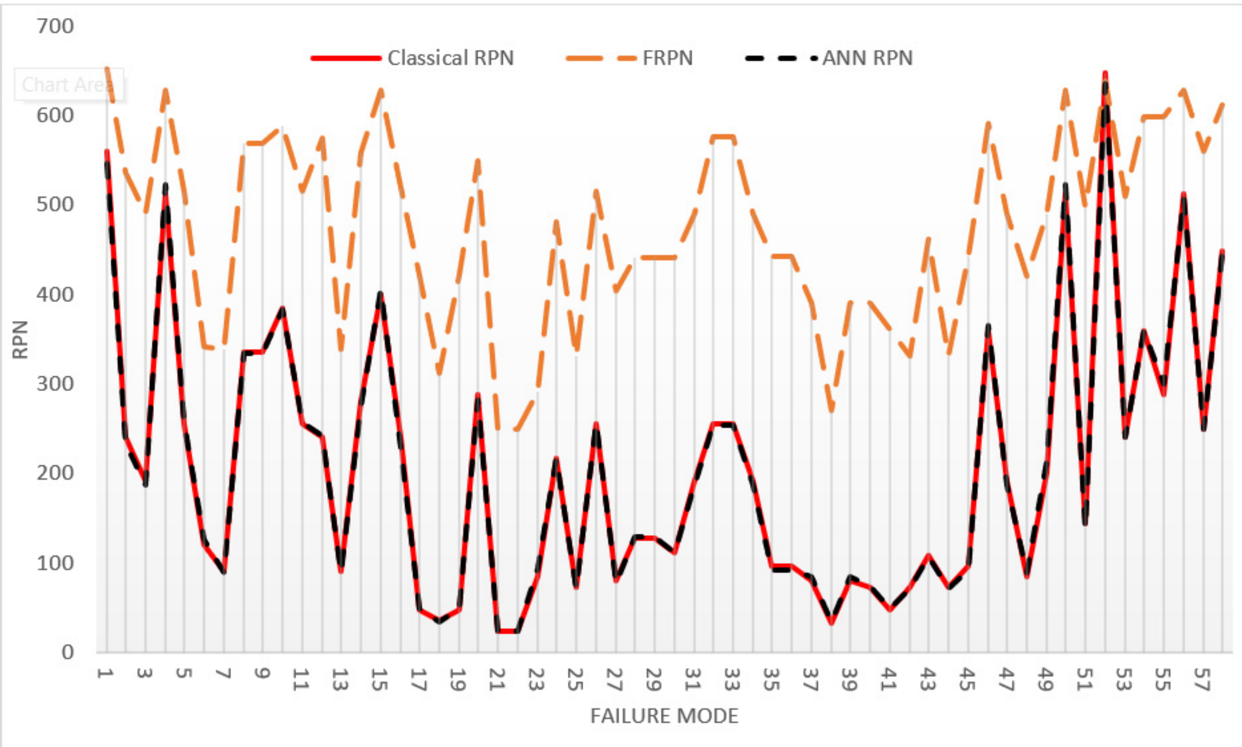



**Figure 12.** RPN values based on three methods vs. Failure modes.

This higher accuracy can be interpreted by the fact that the relationship between input and output data in the fuzzy model is represented as linguistic variables. It is also considering the importance of each parameter to identify the risk. Therefore, the suggested methods can eliminate the shortcomings of the classical method and subsequently provide outputs with higher reliability, applicability, and accuracy.

Since the results of the suggested methods are revealing acceptable accuracy, the models can be implemented at the company. The advantage of the suggested methods, compared to the classical one, is that they replace the human interference in the process and changes the decision-making to be automated, which leads to saving cost, time, resources, and enhances recognition to failures.

## 5. Conclusions

In this research, Fuzzy logic and artificial neural network have been employed to improve failure modes by automatically determining the failure and evaluating the RPN to identify the root cause during busbar production. Three inputs were used to predict values for the RPN these inputs namely severity, occurrence, and detection. The models demonstrated relatively high accuracy, which can be integrated and implemented to improve the company's risk assessment approach. The main reason for this research was to experience new models based on ANN and a FIS. The case study results on the busbar production line showed that the suggested models FIS and ANN can avert the shortcomings of classical risk assessment methods, such as the duplicity in RPN results. In addition, the relationship between input and output in the proposed fuzzy model was described as linguistic variables, which are more realistic in describing the actual conditions, unlike the classic model. Moreover, FIS model has revealed efficient prediction for output, which simplify the decision-making process. ANN model also demonstrated a positive response in prediction, but because of the black box behavior of ANN, some errors in predictions have occurred. Using the machine learning features offers optimal solutions to detect the failure efficiently and inform the quality team immediately to serious problems or by updating the quality checklists in the production line within a reasonable time. Using these methods improves the ability of the quality team to deal with any failure data smoothly and quickly. The features of this technology are not limited, but also could be used to connect failures and defects directly to the responsible machine or operator by integrating the algorithm in the production system once the failure has occurred. Meanwhile, it is paramount to highlight the factors that affect the accuracy of the developed models, such as incorrect evaluation for FMEA or ambiguous data. Therefore, setting the correct inputs leads to acquiring high-quality predictions. For example, in the case of fuzzy, it's very important to set the correct evaluation for three parameters to create a correct linguistic membership, and it is the same for ANN, where the accurate inputs and large enough dataset means accurate training and consistent results.

**Author Contributions:** S.N. (Conceptualization, Methodology, Investigation, Writing—Original Draft, Writing—Review & Editing). M.B.S. (Conceptualization, Supervision, Validation). I.H. (Supervision, Project administration). M.D. (Supervision, Project administration). All authors have read and agreed to the published version of the manuscript.

**Funding:** This work was supported by the Stipendium Hungaricum Programme and by the Mechanical Engineering Doctoral School, Hungarian University of Agriculture and Lifesciences, Gödöllő, Hungary.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Appendix A

**Table A1.** Classical failure mode and the results of RPN in three methods.

| Failure Mode | Occurrence | Severity | Detection | Classical RPN | FRPN | ANN-RPN |
|---|---|---|---|---|---|---|
| 1 | 7 | 8 | 10 | 560 | 651.5611 | 545.9408 |
| 2 | 5 | 8 | 6 | 240 | 535.9268 | 232.6222 |
| 3 | 6 | 8 | 4 | 192 | 489.9969 | 187.1682 |
| 4 | 8 | 8 | 8 | 512 | 628.737 | 523.1866 |
| 5 | 8 | 8 | 4 | 256 | 515.6287 | 257.438 |
| 6 | 8 | 5 | 3 | 120 | 342.2019 | 126.3246 |
| 7 | 6 | 5 | 3 | 90 | 338.8225 | 88.3889 |
| 8 | 6 | 8 | 7 | 336 | 569.1328 | 333.7609 |

**Table A1.** *Cont.*

| Failure Mode | Occurrence | Severity | Detection | Classical RPN | FRPN | ANN-RPN |
|---|---|---|---|---|---|---|
| 9 | 6 | 8 | 7 | 336 | 569.1328 | 333.7609 |
| 10 | 6 | 8 | 8 | 384 | 587.5532 | 383.0731 |
| 11 | 8 | 8 | 4 | 256 | 515.6287 | 257.438 |
| 12 | 3 | 8 | 10 | 240 | 574.3771 | 241.7017 |
| 13 | 6 | 5 | 3 | 90 | 338.8225 | 88.3889 |
| 14 | 5 | 8 | 7 | 280 | 557.7503 | 275.2798 |
| 15 | 5 | 10 | 8 | 400 | 628.3222 | 405.5927 |
| 16 | 6 | 8 | 5 | 240 | 519.0588 | 228.9174 |
| 17 | 6 | 8 | 1 | 48 | 421.2735 | 48.2871 |
| 18 | 6 | 6 | 1 | 36 | 311.2224 | 34.3957 |
| 19 | 6 | 8 | 1 | 48 | 421.2735 | 48.2871 |
| 20 | 6 | 8 | 6 | 288 | 548.6954 | 281.7224 |
| 21 | 6 | 4 | 1 | 24 | 248.7806 | 24.323 |
| 22 | 6 | 4 | 1 | 24 | 248,7806 | 24.323 |
| 23 | 7 | 4 | 3 | 84 | 290.5127 | 93.0517 |
| 24 | 6 | 6 | 6 | 216 | 481.602 | 216.9044 |
| 25 | 6 | 6 | 2 | 72 | 331.5981 | 71.087 |
| 26 | 8 | 8 | 4 | 256 | 515.6287 | 257.438 |
| 27 | 5 | 8 | 2 | 80 | 403.3139 | 77.649 |
| 28 | 4 | 8 | 4 | 128 | 441.5676 | 128.5023 |
| 29 | 4 | 8 | 4 | 128 | 441.5676 | 128.5023 |
| 30 | 4 | 7 | 4 | 112 | 441.5676 | 111.3022 |
| 31 | 6 | 8 | 4 | 192 | 489.9969 | 187.1682 |
| 32 | 4 | 8 | 8 | 256 | 576.4116 | 254.2345 |
| 33 | 4 | 8 | 8 | 256 | 576.4116 | 254.2345 |
| 34 | 6 | 8 | 4 | 192 | 489.9969 | 187.1682 |
| 35 | 6 | 8 | 2 | 96 | 443.0008 | 92.6944 |
| 36 | 6 | 8 | 2 | 96 | 443.0008 | 92.6944 |
| 37 | 4 | 10 | 2 | 80 | 390.9377 | 84.718 |
| 38 | 4 | 4 | 2 | 32 | 269.9129 | 33.5688 |
| 39 | 4 | 10 | 2 | 80 | 390.9377 | 84.718 |
| 40 | 4 | 9 | 2 | 72 | 390.9377 | 74.3005 |
| 41 | 4 | 6 | 2 | 48 | 361.1775 | 48.4972 |
| 42 | 6 | 6 | 2 | 72 | 331.5981 | 71.087 |
| 43 | 6 | 9 | 2 | 108 | 462.0342 | 106.4877 |
| 44 | 6 | 6 | 2 | 72 | 331.5981 | 71.087 |
| 45 | 6 | 8 | 2 | 96 | 443.0008 | 92.6944 |
| 46 | 6 | 6 | 10 | 360 | 591.5751 | 365.5352 |
| 47 | 6 | 8 | 4 | 192 | 489.9969 | 187.1682 |
| 48 | 3 | 7 | 4 | 84 | 420 | 88.4474 |
| 49 | 4 | 10 | 5 | 200 | 490 | 214.2713 |
| 50 | 8 | 8 | 8 | 512 | 628.737 | 523.1866 |
| 51 | 3 | 6 | 8 | 144 | 498.0242 | 138.3124 |
| 52 | 9 | 9 | 8 | 648 | 639.2029 | 635.506 |
| 53 | 6 | 5 | 8 | 240 | 508.9993 | 240.1423 |
| 54 | 5 | 9 | 8 | 360 | 599.0759 | 359.0091 |
| 55 | 4 | 9 | 8 | 288 | 599.0759 | 299.4594 |
| 56 | 8 | 8 | 8 | 512 | 628.737 | 508.4506 |
| 57 | 5 | 5 | 10 | 250 | 559.997 | 249.7707 |
| 58 | 7 | 8 | 8 | 448 | 612.0462 | 445.5558 |

**Table A2.** Failure mode priority for classical method, fuzzy method and ANN method.

| Priority | Classical RPN | Failure Mode (FM) | Priority | FRPN | Failure Mode (FM) | Priority | ANN-RPN | Failure Mode (FM) |
|---|---|---|---|---|---|---|---|---|
| 1 | 648 | 52 | 1 | 651.5611 | 1 | 1 | 635.506 | 52 |
| 2 | 560 | 1 | 2 | 639.2029 | 52 | 2 | 545.9408 | 1 |
| 3 | 512 | 4 | 3 | 628.737 | 4 | 3 | 523.1866 | 4 |
| 3 | 512 | 50 | 3 | 628.737 | 50 | 3 | 523.1866 | 50 |
| 3 | 512 | 56 | 3 | 628.737 | 56 | 4 | 508.4506 | 56 |
| 4 | 448 | 58 | 4 | 628.3222 | 15 | 5 | 445.5558 | 45 |
| 5 | 400 | 15 | 5 | 612.0462 | 58 | 6 | 405.5927 | 15 |
| 6 | 384 | 10 | 6 | 599.0759 | 54 | 7 | 383.0731 | 10 |
| 7 | 360 | 46 | 6 | 599.0759 | 55 | 8 | 365.5352 | 46 |
| 7 | 360 | 54 | 7 | 591.5751 | 46 | 9 | 359.0091 | 54 |
| 8 | 336 | 8 | 8 | 587.5532 | 10 | 10 | 333.7609 | 8 |
| 8 | 336 | 9 | 9 | 576.4116 | 32 | 10 | 333.7609 | 9 |
| 9 | 288 | 20 | 9 | 576.4116 | 33 | 11 | 299.4594 | 55 |
| 9 | 288 | 55 | 10 | 574.3771 | 12 | 12 | 281.7224 | 20 |
| 10 | 280 | 14 | 11 | 569.1328 | 8 | 13 | 275.2798 | 14 |
| 11 | 256 | 5 | 11 | 569.1328 | 9 | 14 | 257.438 | 5 |
| 11 | 256 | 11 | 12 | 559.997 | 57 | 14 | 257.438 | 11 |
| 11 | 256 | 26 | 13 | 557.7503 | 14 | 14 | 257.438 | 26 |
| 11 | 256 | 32 | 14 | 548.6954 | 20 | 15 | 254.2345 | 32 |
| 11 | 256 | 33 | 15 | 535.9268 | 2 | 15 | 254.2345 | 33 |
| 12 | 250 | 57 | 16 | 519.0588 | 16 | 16 | 249.7707 | 57 |
| 13 | 240 | 2 | 17 | 515.6287 | 5 | 17 | 241.7017 | 12 |
| 13 | 240 | 12 | 17 | 515.6287 | 11 | 18 | 240.1423 | 53 |
| 13 | 240 | 16 | 17 | 515.6287 | 26 | 19 | 232.6222 | 2 |
| 13 | 240 | 53 | 18 | 508.9993 | 53 | 20 | 228.9174 | 16 |
| 14 | 216 | 24 | 19 | 498.0242 | 51 | 21 | 216.9044 | 24 |
| 15 | 200 | 49 | 20 | 490 | 49 | 22 | 214.2713 | 49 |
| 16 | 192 | 3 | 21 | 489.9969 | 3 | 23 | 187.1682 | 3 |
| 16 | 192 | 31 | 21 | 489.9969 | 31 | 23 | 187.1682 | 31 |
| 16 | 192 | 34 | 21 | 489.9969 | 34 | 23 | 187.1682 | 34 |
| 16 | 192 | 47 | 21 | 489.9969 | 47 | 23 | 187.1682 | 47 |
| 17 | 144 | 51 | 22 | 481.602 | 24 | 24 | 138.3124 | 51 |
| 18 | 128 | 28 | 23 | 462.0342 | 43 | 25 | 128.5023 | 28 |
| 18 | 128 | 29 | 24 | 443.0008 | 35 | 25 | 128.5023 | 29 |
| 19 | 120 | 6 | 24 | 443.0008 | 36 | 26 | 126.3246 | 6 |
| 20 | 112 | 30 | 24 | 443.0008 | 45 | 27 | 111.3022 | 30 |
| 21 | 108 | 43 | 25 | 441.5676 | 28 | 28 | 106.4877 | 43 |
| 22 | 96 | 35 | 25 | 441.5676 | 29 | 29 | 93.0517 | 23 |
| 22 | 96 | 36 | 25 | 441.5676 | 30 | 30 | 92.6944 | 35 |
| 22 | 96 | 45 | 26 | 421.2735 | 17 | 30 | 92.6944 | 36 |
| 23 | 90 | 7 | 26 | 421.2735 | 19 | 30 | 92.6944 | 45 |
| 23 | 90 | 13 | 27 | 420 | 48 | 31 | 88.4474 | 48 |
| 24 | 84 | 23 | 28 | 403.3139 | 27 | 32 | 88.3889 | 7 |
| 24 | 84 | 48 | 29 | 390.9377 | 37 | 32 | 88.3889 | 13 |
| 25 | 80 | 27 | 29 | 390.9377 | 39 | 33 | 84.718 | 37 |
| 25 | 80 | 37 | 29 | 390.9377 | 40 | 33 | 84.718 | 39 |
| 25 | 80 | 39 | 30 | 361.1775 | 41 | 34 | 77.649 | 27 |
| 26 | 72 | 25 | 31 | 342.2019 | 6 | 35 | 74,3005 | 40 |
| 26 | 72 | 40 | 32 | 338.8225 | 7 | 36 | 71.087 | 25 |
| 26 | 72 | 42 | 32 | 338.8225 | 13 | 36 | 71.087 | 42 |
| 26 | 72 | 44 | 33 | 331.5981 | 25 | 36 | 71.087 | 44 |
| 27 | 48 | 17 | 33 | 331.5981 | 42 | 37 | 48.4972 | 41 |
| 27 | 48 | 19 | 33 | 331.5981 | 44 | 38 | 48.2871 | 17 |
| 27 | 48 | 41 | 34 | 311.2224 | 18 | 38 | 48.2871 | 19 |
| 28 | 36 | 18 | 35 | 290.5127 | 23 | 39 | 34.3957 | 18 |
| 29 | 32 | 38 | 36 | 269.9129 | 38 | 40 | 33.5688 | 38 |
| 30 | 24 | 21 | 37 | 248.7806 | 21 | 41 | 24.323 | 21 |
| 30 | 24 | 22 | 37 | 248.7806 | 22 | 42 | 24.323 | 22 |

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