Nadia BELU[*], Laurenţiu IONESCU[*]

APPLICATION OF FUZZY LOGIC WITH GENETIC ALGORITHMS TO FMEA METHOD

Failure Mode and Effect Analysis (FMEA) is one of the well-known techniques of quality management that is used for continuous improvement in product or process design. One important issue of FMEA is the determination of the risk priorities of failure modes. The purpose of this paper is to compare three different methods for prioritizing failure modes in a process FMEA study. These methods are traditional approach, fuzzy logic and Genetic Algorithms using a risk-cost model of FMEA – to estimate the weight of risk factors. According to the findings, the integration of Genetic Algorithms and fuzzy revealed a difference in prioritizing failure modes among the methods. Because these methods eliminate some of the shortcomings of the traditional approach, they are useful tools in identifying the high priority failure modes. They can also provide the stability of process assurance.

Key words: FMEA, Fuzzy Logic, Genetic Algorithm, Costs, Risk Priority Number

1. INTRODUCTION

In today's hard economic conditions, companies must ensure quality products delivered on time at a competitive price. To achieve it companies always appeal to various quality planning methods, at the same time ensuring that their suppliers do this.

In practice, there are two main groups of methods of quality planning. The first is a group of preventive methods. Their goal is already at the design stage to prevent the occurrence of noncompliance, the consequences of which would be noticeable only in the later stages of production, or even exploitation. The second

---

[*] University of Pitesti, 110040 Pitesti Str. Targul din Vale, nr.1, Arges, Romania.

group of methods of quality planning is a method to design the process parameters. These methods are particularly important for obtaining the best possible technical and economic effects, while maintaining the desired level of product quality [11].

One of the most important preventive methods is Failure Mode and Effects Analysis (FMEA). It is a methodology for risk management and quality improvement aimed at identifying potential causes of failure of products and processes, their quantification by risk assessment, ranking of the problems identified according to their importance, and the determination and implementation of related corrective actions.

The traditional FMEA determines the risk priority of each failure mode using the Risk Priority Numbers (RPN), which can be obtained as a product of three risk factors, namely Severity (S), Occurrence (O) and Detection (D) [6]. Unfortunately, the crisp RPN method shows some important limitations when FMEA is applied in real-world cases. Therefore, a number of approaches have been suggested in the literature to enhance the FMEA methodology, such as technique for ordering preference by similarity to ideal solution (TOPSIS) [3], decision making trial and evaluation laboratory (DEMATEL) [13], grey theory [4, 9], analytic hierarchy process (AHP) [2], data envelopment analysis (DEA) [5], Monte Carlo [1], fuzzy logic
[7, 8, 9, 12, 14].

One of most critical aspects of the FMEA methodology, which is greatly contested by the authors, is that this kind of analysis fails to take into consideration extremely remarkable factors, such as the economic aspect of the failure modes.

In this study, a process FMEA data of a welding process is used. Prioritization of the failure modes will be estimated by 3 different methods and the results of these methods will be compared with each other. First method is the traditional approach, second method is the fuzzy FMEA and the third method is the Genetic Algorithms (GA) using a risk-cost model of FMEA. We applied the GA in FMEA analysis to determine the risk of a process so as the total quality cost – and here we are also talking about the failures costs and the failures prevention and quality appraisal costs – is to be minimal.

2. CLASSICAL APPLICATION OF PROCESS FAILURE MODE EFFECT ANALYSIS

In the first part of the study a classical application of Process FMEA has been realized for the welding process. For this process the FMEA team identified 31 failure modes with different potential causes. Risk Priority Numbers (RPNs) of the failure modes are calculated. The failures with the highest RPN values are pre-

sented (64, 72, 80, and 128). Some of the data can be seen in Table 3. All 31 items are not given in this table.

3. FUZZY FMEA APPLICATION

The methodology of the fuzzy RPNs is based on fuzzy set theory. In 1965, Zadeh proposed fuzzy set theory [15], and later established fuzzy logic based on fuzzy sets. The three inputs Severity (S), Occurrence (O) and Detection (D) are fuzzified and evaluated in a fuzzy inference engine built on a consistent base of IF-THEN rules. The fuzzy output is defuzzified to get the crisp value of the RPN that will be used for a more accurate ranking of the potential risks.

The fuzzy logic toolbox of Matlab software program has been used in calculating the values of RPN. A model was established for the FMEA technique having 3 inputs and 1 output variable, and given in Fig. 1.

Five categories were associated to each fuzzy set: VL (very low), L (low), M (moderate), H (high) and VH (very high). The output of the fuzzy system, FRPN, was scaled in the range 0...1000 in order to be compatible with the previous results.
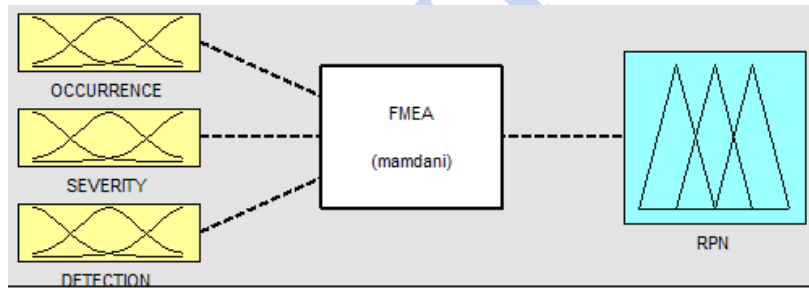

Fig. 1. The Fuzzy FMEA model

Table 1 presents the inference rules adopted for this application, based on expert knowledge, a total of 125 fuzzy rules ($5 \times 5 \times 5$).

Here are given some of the rules as an example. IF occurrence IS very low AND severity IS moderate AND detection IS very high then RPN IS moderate.

For the Occurrence and Severity input variables was used Gaussian membership function (Eq. 1) defined by two parameters respectively center c and width σ. Gaussian membership function can lead to smooth, continuously differentiable hypersurfaces of a fuzzy model, also it facilitates theoretical analysis of a fuzzy system because it is continuously and infinitely differentiable, i.e., it has derivatives of any grade.

$$\mu_A(x) = \exp\left\{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2\right\} \qquad (1)$$

$$\mu_A(x) = \frac{1}{1+\left|\dfrac{x-c}{a}\right|^{2b}} \qquad (2)$$

For the Detection input variable was used Cauchy membership function (generalized bell) (Eq. 2) with the three parameters a, b, c.

Table 1. Inference rules

Occurrence: VL						
FUZZY RPN		*Severity*				
		VL	L	M	H	VH
Detection	VL	VL	VL	VL	VL	L
	L	VL	VL	VL	L	L
	M	VL	VL	L	L	M
	H	VL	L	L	M	M
	VH	L	L	M	M	H

Occurrence: L						
FUZZY RPN		*Severity*				
		VL	L	M	H	VH
Detection	VL	VL	VL	VL	L	L
	L	VL	VL	L	L	M
	M	VL	L	L	M	M
	H	L	L	M	M	H
	VH	L	M	M	H	H

Occurrence: M						
FUZZY RPN		*Severity*				
		VL	L	M	H	VH
Detection	VL	VL	VL	L	L	M
	L	VL	L	L	M	M
	M	L	L	M	M	H
	H	L	M	M	H	H
	VH	M	M	H	H	VH

Occurrence: H						
FUZZY RPN		*Severity*				
		VL	L	M	H	VH
Detection	VL	VL	L	L	M	M
	L	L	L	M	M	H
	M	L	M	M	H	H
	H	M	M	H	H	VH
	VH	M	H	H	VH	VH

Probabilitate apariţie: VH						
FUZZY RPN		*Severity*				
		VL	L	M	H	VH
Detection	VL	L	L	M	M	H
	L	L	M	M	H	H
	M	M	M	H	H	VH
	H	M	H	H	VH	VH
	VH	H	H	VH	VH	VH

Mamdani min/max method of inference mechanism (input method: min; aggregate method: max) was used and the results were defuzzified by center of gravity method. There are different algorithms for defuzzification as well. These are Center of Gravity, Center of Gravity for Singletons, Center of Area, Left Most Maximum, and Right Most Maximum.

Among these algorithms the most popular one is the center of gravity (centroid) technique. It finds the point where a vertical line would slice the aggregate set into two equal masses.

As to the types of failure, the fuzzy RPN values provided in the model are given in Table 3 in comparison with the RPN values of classical FMEA and FMEA based on Genetic Algorithms.

4. FMEA COST MODEL BY GENETIC ALGORITHM

Genetic algorithms (GA) can be used to search for solutions difficult to obtain by other conventional methods, in different areas. They can be run on a computer or can be accelerated on parallel hardware structures [10]. One of the cases when the genetic algorithms are suitable is the optimization problem – finding the optimal solutions. Finding the optimum is a very difficult issue, especially when many different criteria are needed to be considered: that's the situation when we're talking of a multi-criteria analysis for systems.

In this case, we are faced with such a problem. On one side, we have the problem of risk analysis that a production process involves from the perspective of the failures that can occur. On the other side, the costs issue must be considered thus an economic analysis is needed. Finding the optimum is crucial, meaning finding a solution with a risk degree accepted by the client but also viable, economically speaking.

In the proposed model we suppose that failures which will not cause deaths or human injuries are considered in terms of economic evaluation. These kinds of causes (for example with a value of Severity of 9 or 10) must be eliminated in any case, regardless of any economical consideration. The multi-criteria analysis starts only when the failures severity is less than 8. This kind of failures goes in the class where a cost-risk analysis is required and the search of an optimum is made. The problem of finding an optimum is basically the finding of a risk level that is accepted by the client where the failure, prevention and evaluation costs added together, so the total cost, is minimal.

4.1. Costs of quality

Cost of quality is a measurement used for assessing the waste or loss from a defined process. These costs are significant and can be significantly reduced or avoided. Most cost of quality measurements utilize 4 categories of costs:

Internal failure costs (C_i) are associated with internal losses before the product is supplied to the client, are defined by the relation:

$$C_i = n \times P_a \times (1 - P_d) \times C_{di} \tag{3}$$

External failure costs (C_e) occur outside of the process being analyzed. These costs are usually discovered by or affect third parties such as clients, are given by the relation:

$$C_e = n \times P_a \times P_d \times C_{de} + C_{\text{img}} \tag{4}$$

where n is the items produced per batch, P_a the probability of a failure occurring, P_d the probability of the failure not to be detected, C_{di} the internal cost per failure, C_{de} the external cost per failure and C_{img} cost of the firm image (loss of reputation).

Preventive costs are associated with the prevention of future losses due to poor quality, such as unplanned problems, lost opportunities and waste.

Assessment or appraisal costs are those associated with measurement and assessment of a process. These are usually designed to find quality problems before the product or service is delivered to the client or to improve the quality of the product.

$$C_{\text{prev–app}} = n_{\text{equip}} \times c_{\text{equip}} + n_{\text{pers}} \times c_{\text{pers}} \tag{5}$$

where n_{equip} is the number of equipment used in the production process to prevent the failures, for inspections, c_{equip} is the cost of the equipment, n_{pers} is the number of persons engaged in the prevention of failures (for training) and c_{pers} is the cost assigned per person.

4.2. Coding scheme used

The proposed solution in this paper, does not exclude at all the classic FMEA approach. That is because the traditional FMEA reports are still commonly used. That is why we are still using the traditional FMEA parameters S, O and D and the expression of risk assessment is still the classic one.

Instead, the genetic algorithm is the one that after having established values in the acceptable interval for the three parameters, for each failure mode, is assessing the risk by reporting it to the failures costs and also the failures prevention and quality evaluation costs.

By using the presented costs formulas, we are getting different risk assessments reported to the cost. So, we are not changing the risk formula or the parameters frame from the FMEA traditional model but we are using the genetic algorithms to find the optimal solutions for the FMEA parameters so as the total cost of quality which includes the failures costs and the failures prevention and quality evaluation costs is minimal. Something like this would not be possible with the deterministic methods because they do not establish a risk-cost report.

The primary use of the algorithm is to determine the risk of a manufacturing process so as the total quality cost – and here we are also talking about the failures costs and the failures prevention and quality evaluation costs – is minimal.

The gene is coding the tiniest unit in the solution. It is always a number. If a chromosome is revealed by the FMEA parameters for a single failure mode, the gene is one of those factors. The structure of a specimen is presented in Fig. 2.

Fig. 2. Encoding the problem risk-cost analysis with genetic algorithms

As we can see, the specimen is the FMEA analysis. Each chromosome is coding a failure mode. The gene represents a single FMEA parameter. The solution that we are looking for, the one that has been codified inside the individual, is called in specific terminology Phenotype (alongside the other possible solutions) while his "genetic code" is called Genotype.

4.3. Parameters of genetic algorithm in the risk model

After encoding the problem the next step is the parameterization of the algorithm to resolve our problem. The genetic algorithm has a set of parameters that must be established by such a planner as well as the encoding scheme.

Setting the parameters is the second major step that must be followed while working with the genetic algorithms. The parameters of the genetic algorithm that we have used in the cost-risk model are given in Table 2.

Table 2. Parameters of genetic algorithm used in the risk-cost model

Parameter	Value
Number of individuals/generation	10
Maximum number of generations	500
Method of selection (for interbreeding)	roulette wheel
Number of pairs at interbreeding/generation (rate of interbreeding)	1
Number of points of interbreeding	1
Selection method at mutation	random
Mutation rate	0.3
Assessment function	cost minimization
Selection method of the replaced individual	elitist (the weakest is replaced)

4.4. Running the genetic algorithm

After establishing the parameters of the genetic algorithm running the algorithm is taking place using the cost based assessment for an optimum risk analysis. In the diagram from the Fig. 3 are shown the steps for running the algorithm.

In the first place, it all starts from the established failure modes for a certain manufacturing process. These failure modes are automatically retrieved from a database composed by the experts.

This means that anytime the process changes, the database is updated and the algorithm will run to obtain the FMEA analysis for the new process. So our solution is not dependent on a certain process or certain failure mode. In database each failure mode has assigned intervals allowed for S and D. During evolution algorithm (search solution) are obtained S and D and are determined the internal and the external costs on the market as well as the prevention costs (for each failure mode). In this moment is taking place the establishment of the number of chromosomes of an individual.

After this preliminary stage, the launching of the genetic algorithm throws the initialization of the generation 0, the first population of individuals. The initialization is random, for each gene, but respecting the demanded range. After the achievement of the first generation (generation 0) the evolutionary loop is starting. In the first place, the evaluation of that population is taking place (in our case it is

the generation 0). The evaluation represents calculating the failure and prevention and appraisal costs and comparing them. The fitness is obtained by decreasing in the module these two costs. After this assessment, we have a fitness vector, which has on each position the fitness value for each individual.
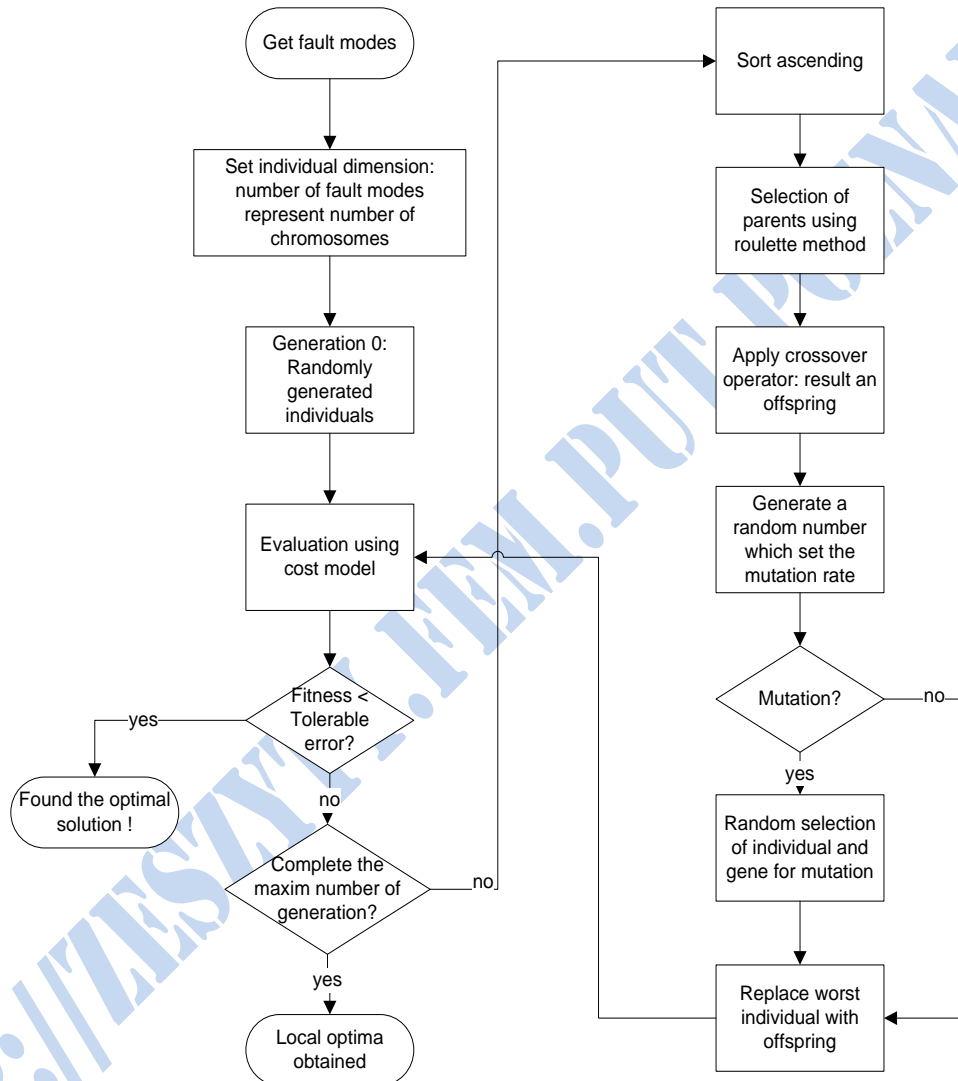

Fig. 3. Diagram of the genetic algorithm to determine the FMEA based on the risk-cost analysis

In the testing stage, we also check if the evolution process is over, through convergence to the searched optimum solution, if one of the individuals has its fitness

value under the limit of the maximum permissible error (in this case +/–50) or through convergence to a local optimum when the number of generations has been run is bigger than the maximum allowed. Through the second case, we have a solution that is the best, so far, but is not the optimum. If this matter is not convenient, the evolution process can restart once again, the generation 0 will have other values than the generation 0 from the previous process.

If the evolutionary loop is not over (the optimum has not been found and maximum allowed number of generations has not been reached), the classification of the individuals is taking place after the fitness vector. Sorting is necessary for the next stage, namely the selection. Through the selection the two parents will be chosen for the crossover operator.

The crossover is carried out through random selection of the crossover point. The resulting offspring will be from this moment the eleventh individual of the population (which initially had 10 individuals).

The next genetic operator, the mutation, is enabled for the current generation randomly, according to the rate of mutation – as we showed it is not necessarily a mutation of the generation. If the mutation is occurring, then an individual and one of his genes is chosen randomly which will suffer the mutation. The mutation represents the changing of the gene condition randomly but respecting the valid interval of values. After the mutation, there are still eleven individuals; the mutation is an operator that is changing the condition of an individual, it does not lead to a new individual. After this last genetic operator has been applied, the resulting offspring (the eleventh individual) will replace the randomly weakest one resulting from the assessment. So at the end we have a population with 10 individuals.

Another specific element of the run algorithm for our problem is the fact that we'll have the same number of individuals and it won't change during the evolution process (just like the generation 0).

The evolution process is restarted from the assessment and it is running until the end of the evolution, as shown.

4.5. The achieved results

Alongside the temporarily displayed results – some of them very hard to understand – as well as the final report during the evolution, the program allows saving into a file the information that must be investigated.

The Risk Priority Number (RPN) has been monitored during the evolution. Its evolution for a process with 7 failure modes is presented in Fig. 4.

It can be seen that it's spreading to a big scale of values at the beginning, but after that, as the algorithm converges we can see that the scale is getting smaller. The calculations have been done on a RPN of an individual with the arithmetic average of the RPN for each failure mode.

It can be observed the evolution of the individual 8 (purple). It started from a medium RPN of below 118 and as the evolution continues (more specifically in the first 15 generations) we have a constant value. After that, the value increases to 129. Finally, all individuals converge to a RPN value around 99.
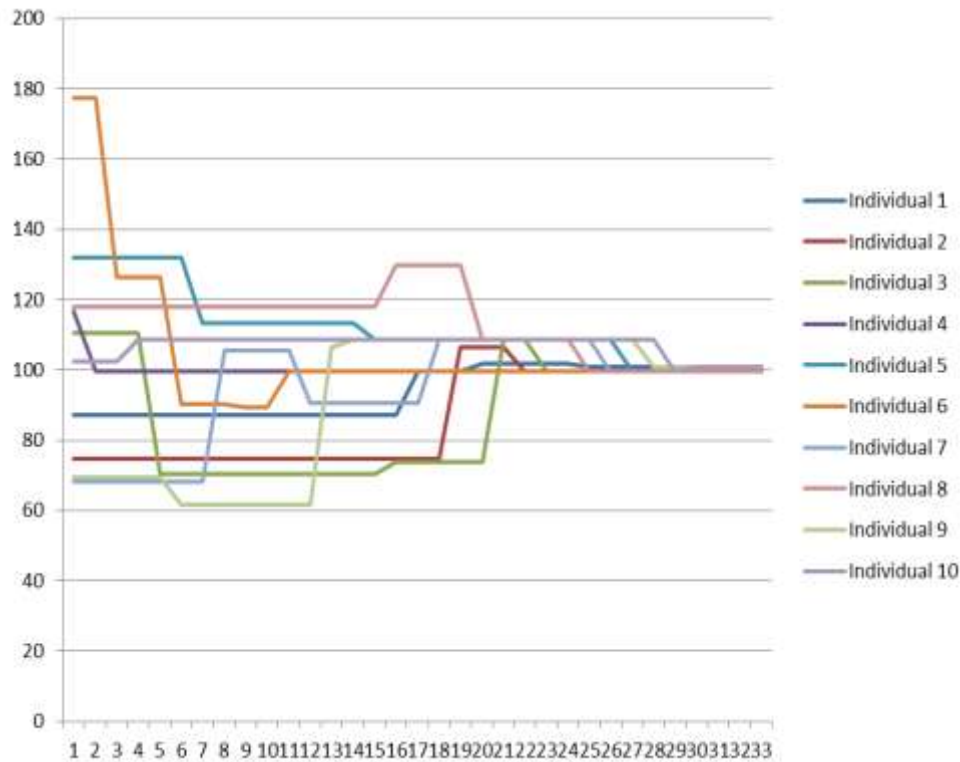

Fig. 4. The evolution of RPN – analysis of process with 7 failure modes, convergence at the generation 33

This is explained by the fact that evolution trains all individuals to an acceptable risk-cost ratio.

At generation 33, individual 8 has been selected which represents the cost report that is most optimum but also with the tiniest risk of all of the populations. This is a perfect situation when the risk and the cost are both very low.

In Fig. 5 we illustrated the evolution of cost in AG.

The optimal cost is found from the 18 generation. The rest of evolution is focused to search RPN for an optimal risk-cost ratio.

In this study, the results of the three applications (classical and the other two) were compared in Table 3. The obtained results, under the assumption of assigning different weights to the risk factors, differ from the other two applications.

For example, "inclusions" failure mode with the potential cause of failure "welding wire stored in unsuitable conditions (moisture, dust)" that is the first in the first two applications (classical and fuzzy FMEA) is not ranked among top five in the third application (FMEA cost model by Genetic Algorithm).
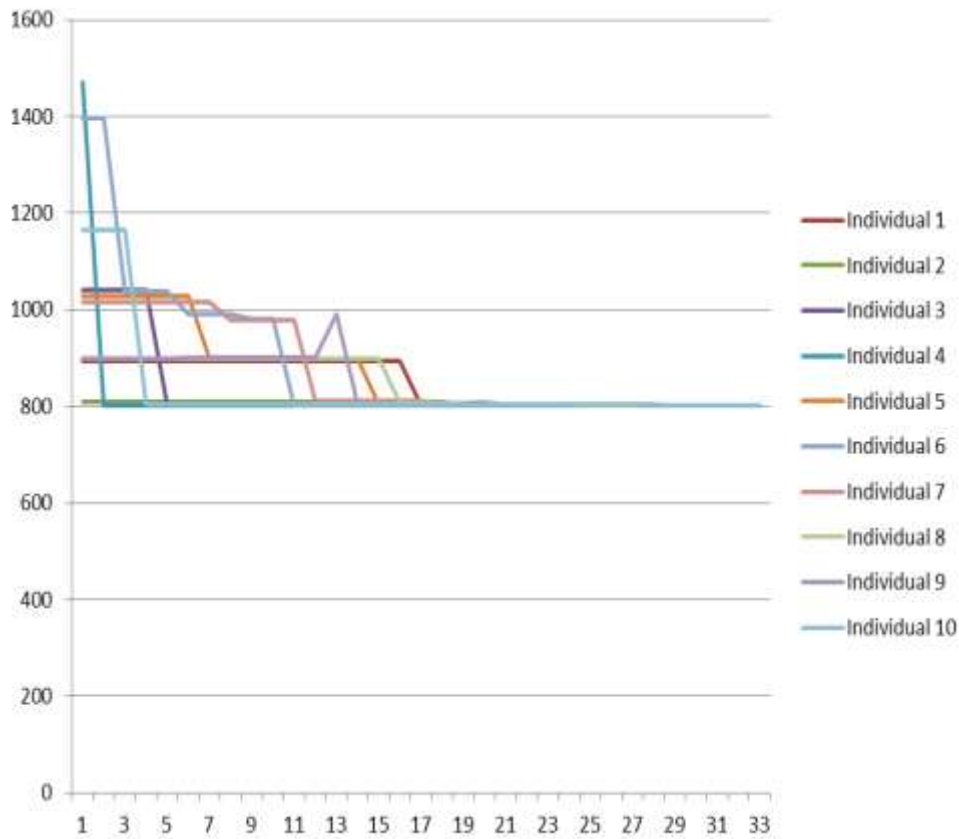

Fig. 5. The evolution of cost – becomes around 800 units for each individual from 18 generation

The results obtained by fuzzy inference provide a hierarchy of potential risks that differs from the ranking established by conventional computation of the RPN.

The fuzzy inference does not allow identical values of RPNs to appear for different sets of risk factors:

− for "cracks" failure mode with the potential cause of failure "thermal shock / cooling too fast": RPN = 48 (ranking 1 is 12); FRPN = 546, (ranking 2 is 3);

− for "insufficient penetration" failure mode with the potential cause of failure "Improper welding parameters": RPN = 48 (ranking 1 is 14); FRPN = 513, (ranking 2 is 15).

Another example is that "insufficient penetration" failure mode with the potential cause of failure "oxidized parts" is placed first in the last application, whereas it was ranking 14–15 in the first two applications.

5. CONCLUSIONS

FMEA, as a very important safety and reliability analysis tool, has been extensively used for examining potential failures in products, processes, designs and services.

Compared with the traditional RPN, the fuzzy FMEA proposed has advantages, for example:
− more risk factors can be included if necessary;
− the relative importance weights of risk factors are taken into consideration in the process of prioritization of failure modes, which makes the proposed FMEA more realistic, more practical and more flexible;
− risk factors and their relative importance weights are evaluated in a linguistic manner rather than in precise numerical values.

The traditional FMEA analysis does not include a financial evaluation of the failure mode. A risk-cost model offers the management opportunity to determine the financial risk of failure modes and to weigh the failure costs with the expenses needed for improvements. Using a model based on costs in FMEA analysis is obtaining a viable alternative with a lower degree of subjectivity in the process of risk assessment.

The genetic algorithms method is given a higher risk coefficient than the one given by the traditional method. That is because with this cost model, the economic aspect of the process is also considered. We also have to consider that the genetic algorithms method is at a global scale for the whole process. Although we have a higher risk coefficient for a failure mode, on a global scale we have a decrease of risk and cost.

The proposed solution offers an alternative with low cost to commercial solutions and provides benefits in terms of cost and time allocated for FMEA analysis.

LITERATURE

[1] Arunraj N.S., Mandal S., Maiti J., *Modeling uncertainty in risk assessment: An integrated approach with fuzzy set theory and Monte Carlo simulation*, Accident Analysis & Prevention, 2013, 55, s. 242-255.

[2] Braglia M., *MAFMA: Multi-attribute failure mode analysis*, International Journal of Quality & Reliability Management, 2000, 17 (9), s. 1017-1033.

[3] Braglia M., Frosolini M., Montanari, R., *Fuzzy TOPSIS approach for failure mode, effects and criticality analysis*, Quality and Reliability Engineering International, 2003, 19 (5), s. 425-443.

[4] Chang C.L., Liu P.H., Wei C.C., *Failure mode and effects analysis using grey theory*, Integrated Manufacturing Systems, 2001, 12 (3), s. 211-216.

[5] Chin K.S., Wang Y.M., Poon G.K.K., Yang J.B., *Failure mode and effects analysis by data envelopment analysis*, Decision Support Systems, 2009, 48 (1), s. 246-256.

[6] Chrysler Corporation, Ford Motor Company, General Motors Corporation, *Potential Failure Modes and Effects Analysis (FMEA). Reference Manual*, 4th ed., 2008.

[7] Guimaraes A.C.F, Lapa C.M.F., *Fuzzy inference to risk assessment on nuclear engineering systems*, Applied Soft Computing, 2007, 7, s. 17-28.

[8] Lertworasirikul S., Fang S.-C., Joines J.A., Nuttle H.L., *Fuzzy data envelopment analysis (DEA): A possibility approach*, Fuzzy Sets and Systems, 2003, 139, s. 379-394.

[9] Liu H.C., Liu L., Bian Q.H., Lin Q.L., Dong N., Xu P.C., *Failure mode and effects analysis using fuzzy evidential reasoning approach and grey theory*, Expert Systems with Applications, 2011, 38, s. 4403-4415.

[10] Mazare A., Ionescu L., Serban G., Barbu V., *Evolvable Hardware with Boolean Functions Network Implementation*, w: *Proceeding of International Conference on Applied Electronics*, IEEE Catalog Number CFP1169A-PRT, Pilsen, September 2011, s. 255--260.

[11] Misztal A., *Quality planning in various sectors companies*, w: *Book of Proceedings of International May Conference on Strategic Management*, University of Belgrad, Bor, Serbia, 2013, s. 778-786.

[12] Rachieru N., Belu N., Anghel D.C., *Improvement of Process Failure Mode and Effects Analysis using Fuzzy Logic*, Applied Mechanics and Materials, 2013, 371, s. 822-826.

[13] Seyed-Hosseini S.M., Safaei N., Asgharpour M.J., *Reprioritization of failures in a system failure mode and effects analysis by decision making trial and evaluation laboratory technique*, Reliability Engineering & System Safety, 2006, 91 (8), s. 872-881.

[14] Tay K.M., Lim C.P., *Application of fuzzy inference techniques to FMEA*, Advances in Intelligent and Soft Computing, 2006, 34, s. 161-171.

[15] Zadeh L.A., *Fuzzy sets*, Information and Control, 1965, 8 (3), s. 338-353.

ZASTOSOWANIE LOGIKI ROZMYTEJ
Z ALGORYTMAMI GENETYCZNYMI DO METODY FMEA

Streszczenie

Analiza przyczyn i skutków wad (FMEA) należy do dobrze znanych technik zarządzania jakością; jest wykorzystywana do ciągłego doskonalenia projektów, produktów lub procesów. Jedną z ważnych kwestii FMEA jest ustalanie priorytetów ryzyka niezgodności. Celem niniejszej pracy jest porównanie trzech metod ustalania poziomu ryzyka niezgodności: podejścia tradycyjnego, logiki rozmytej i algorytmów genetycznych na potrzeby analizy FMEA. Integracja algorytmów genetycznych i logiki rozmytej ujawniła różnicę w ustalaniu znaczenia przyczyn niezgodności. Ponieważ metody te eliminują niektóre wady podejścia tradycyjnego, są użytecznymi narzędziami w identyfikacji przyczyn niezgodności o wysokim ryzyku. Mogą również zapewniać stabilność procesu.