Risk-cost model for FMEA approach through Genetic algorithms – A case study in automotive industry

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Abstract. Failure mode and effects analysis (FMEA) is a proactive method for eliminating the potential failures emerged from various systems such as products, processes, designs, or systems. FMEA utilizes the risk priority number (RPN) to determine the risk priority order of failure modes. RPN is calculated by multiplying the values of three risk factors: severity (S), detection (D) and occurrence (O). Although FMEA techniques are used in different industries in many situations when multiple experts give their opinions about one failure mode, the risk evaluations can be vague and imprecise, which could arise conflicting evidence that is hard to manage. This paper presents a risk-cost analysis model that uses Genetic algorithms to generate an FMEA for the raw materials and finished parts reception process, in automotive industry. Unlike the classic FMEA analysis, in our model the risk factors D and O are determined by resources cost analysis involved in their improvement. Here comes the Genetic algorithm that will determine the optimal cost under an acceptable risk. The proposed solution uses modern information technology for data acquisition (complex event processing), automation of analysis process (artificial intelligence) and long-term support for quality staff in FMEA analysis (real time and batch data analytics).

1. Introduction
The classic FMEA method is based on a brainstorming involving the production, maintenance, methods, logistics and quality engineers that determine the three risk factors: severity (S), detection (D) and occurrence (O) for each failure mode. However, this solution, through the subjectivism that introduces it, can generate defective planning of priorities in the treatment of failure. For this reason, recent research has been focused on improving the FMEA analysis mechanism by using intelligent algorithms. The use of intelligent algorithms to improve FMEA analysis is also presented in paper [1]. As shown here, the fuzzy solution for FMEA optimization leads to a more accurate planning of priorities in dealing with faults compared to classical methods. The fuzzy technique for improving FMEA has become quite used so that [2] presents a fuzzy framework for FMEA. Here is presented a prototype that can help inexperienced users to perform FMEA for quality management improvement, but also as an alternative to "classical" designing, material selection, cost assessment, etc. The use of genetic algorithms in FMEA to determine FMEA factors (especially D and O) is another direction of research. In paper [3] there is shown a solution for the use of diagnostic and prognostic algorithms included in the FMEA analysis. Diagnosis and prognosis algorithms presented here include Genetic algorithm (GA) and precede the...
FMEA analysis itself. They are used to assess the risks and determine FMEA coefficients by decomposing the production system into components. Intelligent analysis involved in FMEA is a research area with results presented in more papers like [4]. Genetic algorithms in combination with fuzzy used in FMEA are presented in paper [5]. Here we have a hybrid fuzzy-GA solution - GA are used to generate rules and reduce them and fuzzy to generate FMEA - and the paper presents a case study in a semiconductor manufacturing process. Also, Genetic algorithms are used combined with more “classical” quality management methods as shown in [6]. This paper presents a solution combining Taguchi optimization with Genetic algorithm. The Taguchi method reduces the number of faults and their complete cancellation is done by GA starting from the Taguchi dataset, reasonably minimized. The solution is applied to processes of welding, damper sealing, washing and painting. The FMEA analysis using costs involved in equipment is presented in the paper [7]. Unlike the solutions presented, our solution uses the GA to investigate a solution space to optimize a multicriteria problem: on the one hand to reduce the risk but at the same time with reduced costs of quality control systems. The algorithm finds one or more solutions with risk and cost acceptable. So, we have a risk-cost problem optimized by Genetic algorithm. To what was presented in the paper [8], the solution proposed here brings improvements through the use of modern IT tools for complex event processing, enterprise service bus, application peripheral interface and Data Service Server that extend the integration capabilities of the industry 4.0 IT infrastructure and present a case study in the automotive industry, a segment of storage of the raw materials, processing and storage of processed parts.

2. System description

The solution proposed in this paper uses an automated FMEA analysis system that considers the risks but also the cost of their reductions by the implementation of the quality control points. Thus, more than just a “classic” FMEA analysis, the proposed solution finds optimum between the risks involved in a manufacturing process and the costs involved in implementing quality control methods in the manufacturing process to decrease the failures. The solution can be applied to a quality management system for a modernized industrial process that has evolved to Industry 4.0.

The proposed system, shown in figure 1, is composed of the following:

- The cost analysis component for quality control points implementation. The implementation of quality control points has the effect of reducing the risk factor (O) and increasing the failure detection capacity (D). The solution presented in this paper allows the acquisition of data related to quality control points and the determination of the costs that the use of control points involves. When applying a method of detecting or reducing the failure occurrence, it is possible to take over, through a specialized communications interface, the costs involved in applying this method. The costs can be entered through a web form, can be retrieved from an already existing computer application via a software connector or can be taken over automatically by analyzing a technical control flow - for example, a sensor-based detection system indicating use of a device.
in fault detection. Regardless of the method used, the IT system developed and presented in this paper allows data acquisition: in the case of web forms, we have a specialized connector and a web service that takes the data from the forms and stores them in a database, if it is connected to the other applications, the system has many connectors for this in an Enterprise Service Bus (ESB) solution; finally, if we are talking about acquiring data from sensors on equipment used in control point, then our solution also has an advanced complex events processing (CEP) module to which any IoT device can be connected. In the paper, a case study is presented in which the use of monitoring devices in quality control points involves an electric power consumption - this is taken over by power consumption sensors and then is provided to our system through the CEP interface. At the same time, there is an interface where the quality engineer or manager can enter the cost per person / day and the cost of maintenance / which involves the use of failure detection equipment for parts that are received in a warehouse.

- The FMEA risk-cost analysis component. This is the main core of our system. The cost data acquired by the first component along with the "classic" FMEA analyzes are stored in a database. From here they are "encoded" in the form of genetic chromosome sequences. Such a sequence consists of two main components: on the one hand the cost component and on the other the risk component - more precisely the factors D and O. The system uses cost data and the impact on factors D and O that were provided by the first component but also makes estimates about D, O and costs generated when a quality control point is introduced in manufacturing point. For example, the introduction of a quality control point at a warehouse of processed parts (threaded pistons) based on their weight measurement to see if they were subjected to the milling process with a control rate of 10 parts per batch of 100 implies a additional average power consumption of 0.8A, cost per operator of 100 RON / person / day and maintenance cost of 2 RON / day - data taken through the first component of the system. Based on this, our system can determine the impact on the factors D and O and what would be the cost if five such control equipment had been introduced, another equipment is introduced in a quality control point or if the control rate would increase to 20 pieces / batch. Such cost-impact estimation solutions on the risk factors are provided by the Genetic algorithm integrated in this component. The objective pursued is to fit into an acceptable cost-risk "green" area - the search for solutions that fall within this area is a multicriteria optimization problem. The genetic algorithm is a class of evolutionary algorithms specialized in solving such search problems. By using this algorithm, the automated analysis component will find one or more risk-cost optimal solutions that will result from two released documents: an FMEA analysis and a cost report generated by the third component of our system, namely reporting module. Details about Genetic algorithm parameter and objective function are presented in annexes.

- The reporting module is the one that generates reports based on the solutions provided by the risk-cost analysis component. From the FMEA risk-cost analysis component, one or several solutions are provided within the allowable area (green area). These solutions are made available to the quality team in the form of two reports (for each solution): an FMEA analysis report and a cost report - both automatically generated. The quality team analyzes the two reports for each solution eventually in collaboration with the beneficiary and decide the accepted solution. By providing several possible risk-cost solutions, the system allows a configuration of the final quality control solution to be used in the production flow.

The following is a demonstration of our system deployment in an automotive production unit at the reception for storing, processing and then folding some parts (pistons). The production segment where our solution was implemented receives the raw materials (un-processed pistons), ensures their machining (by pressing and milling) and then the storage of the processed pistons for future supply. As failure detection methods for this case study we have verification of raw materials (visual) by quality controllers, verification of raw materials by automatic electromechanical weighing systems, verification of the correctness of application of processing by Poka Yoke systems also on automatic weighing with step-by-step warning, visual inspection of finished parts.
Each verification method involves two types of costs: automatically determined dynamics costs such as power electricity consumption and static costs introduced by quality operators such as the man / day fare for the staff involved in the quality control and the maintenance fee / day for equipment.

The acquisition of the dynamic costs – in our case power supply consumption is done through an IoT solution with non-invasive current sensors (clamps sensors that are applied to the power supply cable of the equipment). Our system, through the "cost analysis component", has a Complex Event Processing module specialized in taking data from IOT measuring devices and storing them – everything is done automatically. Complex event processing module has several types of data reception interfaces - http, tcp, smtp, ftp, serial etc. In this case, an http interface is used to retrieve http requests from the measurement devices. Retrieval of the static costs is done through web interfaces and web services that takes the data from the web forms and store them in the database. In our case is used a dedicated Application peripheral interface (API) and Data Service Server (DSS) middleware. In addition, our solution also has an enterprise service bus module that allows data retrieval from other applications that exist in the enterprise's IT infrastructure - this module is not used in the case study presented in this paper but it can be used for future deployments. In the study case presented in the paper, web forms are available, accessible in the enterprise intranet, and web services developed in API and DSS take data about the cost per person / day and maintenance / day. The data is stored in a relational database (MySQL), but DSS allows you to connect to several types of both relation database and NoSQL data base. DSS can also be used as a data source - it is possible to build services that connect to existing databases in the company's IT infrastructure to retrieve data such as static costs.

The stored data can then be analysed by the risk-cost analysis component. The analysis involves running the Genetic algorithm that search the acceptable risk-cost solutions. This analysis takes place automatically, does not require the intervention of any user. The intelligent analysis module with genetic algorithm is integrated into the FMEA risk-cost analysis component described in this paper. The program was done in the server-side JavaScript. Finally, the results from the analysis module are provided as two documents per solution. As we have shown, these two automatically generated documents are an FMEA and a cost analysis. The reporting module and dashboard graph representing the solutions of the algorithm which are presented in this paper were developed in the Typescript client side using the PrimeNG framework.

3. Mathematical relation used in our solution, parameters and objective function of Genetic Algorithm

There are 5 control points which involves equipment and operators. Each control point has an id code which is used to identify it in the next steps (e.g. pwydevice_18595). Each control point has its D factor for a specific failure – obtained from the technical analysis of the performances of control point and from the specific of manufacturing process. In generally, cost of control point reflects D factor: the performant equipment in failure detection which are expensive give a smaller D factor.

For each control point, the daily cost is obtained from the man day cost, the equipment cost and the average consumption of electricity according relation (1):

\[
dayCost = \text{Round}(manDay + equipmentDay + averageConsumption \times 220 \times 0.5)
\]

\(averageConsumption\) is given by sensors in Ampere is multiplied with medium voltage of 220 V to give power consumption in Watts and with 0.5 factor which is price in local monetary unit (RON) per KWatt. So, all values are expressed in RON.

Genetic algorithm uses a coding schema with chromosomes which consist from the control point code (selected from the list with all 5-control points id’s) and a two digits integer number which represents the number of control tests applied to the batch of 100 parts.

\[\text{chromosome} \leftarrow \text{controlPointID} \& \text{numberTests}\]
One individual has a single chromosome. So we have a simple structure of individuals what allow us to use a large number of individuals. In our approach, we use for one generation 1000 individuals. One generation can be divided in 5 groups of individuals for each control point. In our case study, for one single day is possible to control 4 parts: \textit{dailyNoTests}. So, the total cost of the control for a chromosome is (2):

\[
\text{totalCosts} = \frac{\text{numberTests}}{\text{dailyNoTests}} \times \text{dayCost}
\]  

(2)

From \textit{numberTests} is obtained O factor according to the relation (3)

\[
O = \begin{cases} 
\text{Round} \left( \frac{\text{numberTests} \times 10}{\text{maxNumberTests}} \right), & \text{if } \text{numberTests} > 0 \\
10, & \text{if } \text{numberTests} = 0 
\end{cases}
\]

(3)

\text{maxNumberTests} is the maximum value of \textit{numberTests} for a certain control point – is obtained from a control point group of individuals.

S factor for a specific failure is obtained from technical analysis of manufacturing process. S and D factor are inputs in our IT solution.

Finally, for each chromosome is obtained a RPN value and a total cost. Objective function for Genetic algorithm is obtained by bringing RPN and total cost at same level and by applying a weight for each according its importance. In our study case, importance of cost and risk are the same in final decision – weight is same in this case. Target is to obtain individuals with minimum \textit{ObjFunc} value.

\[
\text{ObjFu} = \begin{cases} 
\text{totalCosts} \times \text{normFactor} \times \text{costWeight} + \text{RPN} \times \text{riskWeight}, & \text{if totalCosts} > \text{RPN}, \text{where normFactor} = \frac{\text{maxRPN}}{\text{maxCosts}} \\
\text{totalCosts} \times \text{costWeight} + \text{RPN} \times \text{normFactor} \times \text{riskWeight}, & \text{if totalCosts} < \text{RPN}, \text{where normFactor} = \frac{\text{maxCosts}}{\text{maxRPN}} 
\end{cases}
\]

(3)

Crossover in genetic algorithm is average between \textit{numberTests} of the two parents and mutation is a random selection of a \textit{controlPointID}. For a generation we have crossover rate of 1 and mutation 0.3. Selection method of parents is roulette rule and only two parents are selected for each generation. Size of population is same for each generation, individuals which less fitness from a generation (the biggest value of \textit{ObjFunc}) are removed.

4. Experimental results. A case study
The case study presented in the paper refers to the control applied to a batch of the 100 parts (pistons) that are received, subjected to two technological operations (milling and pressing) and then stored in a warehouse. The quality control checking of the parts is done both on the input batch (raw materials) and on the output batch. One of the 5 quality control points is used for verification. Each quality check point involves a set of equipment and operators. The cost per operator / day, the cost of the equipment / day and the electricity consumption are the costs that are evaluated by the system - presented in table 1.

| WEB form used to insert static costs and to display dynamic costs – capture from WEB interface of our system |
|--------------------|----------------|----------------|
| Average consumption [A] | Man day cost [RON] | Equ. Maintenance/day cost [RON] |
| pwydevice_57943 | 34.36 | 261 | 625 |
| pwydevice_96276 | 75.51 | 456 | 826 |
| pwydevice_8940 | 82.55 | 244 | 524 |
| pwydevice_24561 | 65.13 | 7 | 566 |
| pwydevice_62311 | 4.94 | 17 | 401 |
The total daily cost is derived from static costs and the dynamic cost of electricity consumption – this is shown in figure 2. Next, our system makes a factor D assessment based on the performance of the equipment. The figure 2 provides D factors for each control point.

The Genetic algorithm determines 10 test profiles for each quality control point. From these profiles it is then determined, having the data from the cost analysis component, the total cost of the control point as well as its impact on the O risk factor. Finally, we will have FMEA analysis for all the 10 generated profiles for each control point and cost analysis. Generating RPN, figure 3, is considering the third risk factor S, which represents another input in our system - the determination of the S factor is done starting from a technical analysis of the failure severity.

In the last step the system determines the optimal result (or results) from the profiles and the control point. The optimal result is the one that involves minimal cost / risk. In this case study, cost and risk are taken as two equal components - the weight that each brings to the optimal result is 50%.

This approach was convenient in the case study presented here. The figure 4 shows the evolution of the optimal result for the 10 solutions generated at each control point. The lowest point is the most cost-effective solution. Thus, the analysis will give both the quality control point to be used and the profile it will be approached - in this case a single point of control is desired but the system proposed by us may indicate even more distinct control points.
Figure 4. Optimum results risk – cost for each control point and each profile generated by GA. The green graph which correspond to a control point has a minimum to solution 2 (profile 2) and blue graph which correspond to another control point has minimum for solution 9. This two points are the optimum risk – cost results.

Of course, if a cost-effective control scheme is desired, the cost and risk ratio can be changed to the optimal outcome. For example, the cost could be 60% and the risk 40% of the result - which means that solutions will be sought to reduce the quality control costs more at the expense of rising risk.

All the results presented in the graphs in this section are captures from the system's web interface - the cost web form as well as the system dashboard. The charts with optimal results were displayed for advisory purposes - of course, our system automatically selects the minimum - the solution or solutions that are proposed as the most optimal. Details about the maths behind the charts are presented in annexes.

5. Conclusions and future trends
The paper presents a complete computer solution for risk analysis in a manufacturing process. As shown, the analysis implies both a risk analysis - centralized in an IT solution - and an analysis of the costs that quality control methods pose. Unlike other solutions of this kind, our solution also brings:
- The ability to collect data from different sources through the CEP and ESB solutions;
- Intelligent analysis using Genetic algorithm of quality control methods and cost-benefit optimization;
- Implementation of the solution in a suitable environment to be used in an enterprise intranet - in general the solutions presented in other papers used research-specific environments, the solution which we propose here uses a computer-based production environment - with the development-production paradigms present;
- Our solution offers more possibilities for optimal results - quality and management staff can decide which of the solutions best suited to the company profile.

The paper presents a single case study where the system was used with very good results. As future research directions, we have expanded the scope and set of input data: for example, the data provided by the equipment can be extended by other sensors, other costs can also be found.

6. References
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