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Determination of manufacturing process failures priority under type 2 fuzzy environment: Application of genetic algorithm and Variable neighborhood search

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Abstract
The aim of this research is to propose the two-stage model to select a set of failures that need to be eliminated or reduced which leads to improved reliability and effectiveness of the manufacturing process in the automotive industry. In the first stage, uncertainties under the relative importance of risk factors and costs of manufacturing process downtime due to failure are modeled by type 2 fuzzy sets. The weights vector of risk factors is obtained by analytical hierarchical Process which is extended with type 2 fuzzy sets. Evaluation of risk factors at the level of each identified failure is based on failure mode and effect analysis which is widely used in practice. Determining the set of failures to be eliminated is set as a knapsack problem. The linear fitness function is defined as the ratio of the overall risk priority index and total costs. Maintenance costs incurred due to the realization of failure are limited by the available budget and in this knapsack problem are presented by a linear inequality. The solution to this problem is found by using the Genetic Algorithm and Variable Neighborhood Search. The model is verified with real-life data originating from automotive companies that exist in Serbia. Authors have managed to obtain suitable results on different knapsack problem instances. It is shown that the enhancement of the manufacturing process can be based on the proposed model.

Keywords
Failure mode and effect analysis, selection set of failures, type 2 fuzzy sets, genetic algorithm, variable neighborhood search

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Introduction

Enhancement of the reliability and effectiveness of the manufacturing process can be achieved, among other things, by eliminating potential failures that may occur in the manufacturing process. Failure Mode and Effect Analysis (FMEA) is the most widely used method for detecting, analyzing, and evaluating failures. In practice, this problem is solved in three basic steps. First, potential failures, the causes that lead to their occurrence, and the consequences that occur as a result of the failure realization. After that, a risk assessment is performed, i.e., the priority of identified failures is determined, in order to propose and implement appropriate actions in the final phase, in order to prevent the occurrence of failures or reduce their impact.

The problem of failure analysis is important from several aspects of the business of industrial companies. First of all, the aim of conducting the FMEA analysis is to reduce or eliminate unnecessary delays and downtimes, reduce the occurrence of scrap, and eliminate unsafe procedures and conditions that lead to possible injuries at work, but the implementation of this analysis also has a financial aspect. Therefore, the importance of this analysis is recognized in many branches of the manufacturing industry, and it is primarily important for the automotive industry. For this reason, the application of FMEA analysis is mandatory for all suppliers, i.e., companies that correspond to the automotive supply chain.

Respecting the nature of human thinking, it can be said that decision-makers (DMs) more easily and accurately express their estimates using natural language words

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than precise numbers. The development of type 2 fuzzy sets (IT2FSs) was introduced by[1] allowing vagueness to be represented fairly quantitatively. Some characteristics of IT2FSs are (1) handling of linguistic and numerical uncertainties and (2) the modeling of existing uncertainty in the IT2FSs is not only limited to linguistic variables but also in the definition of membership functions.[2] One of the main shortcomings of the IT2FSs type is that the handling of IT2Fs is significantly complex. To overcome this shortcoming, many authors suggest using the interval type triangular 2 fuzzy numbers (IT2TFNs) that represent a special case of the interval type 2 trapezoidal fuzzy numbers (IT2TrFNs). In this research, uncertainties under the relative importance of risk factors (RFs) and manufacturing downtime identified failures are modeled by IT2TFNs.

There is a number of papers in the literature where elements of the fuzzy pair-wise comparison matrix of relative importance are described by IT2FNs.[2–4] The authors of the above papers suggest that the determination of type 2 fuzzy weights vector should be based on the Buckley method Buckley.[5] In this way, unique solutions are obtained.

In practice, the priority of identified failures is based on the risk priority index (RPN) which is calculated as the product of the values of three risk factors (RFs): severity, occurrence, and detection. Liu et al.[6] defined several shortcomings of conventional FMEA that means affect the accuracy of prioritizing failures. In the relevant literature, many authors have suggested different approaches to improve the shortcomings of the conventional FMEA.[7–10] In this research, assumptions were made that the RFs have different relative importance, by analogy,[11–13] and that their weights are obtained by applying AHP with IT2TFNs.

Based on the results of best practice, it can be argued that during a predetermined planning period, it is not possible to eliminate all identified failures due to limited financial resources. The FMEA team usually bases the order of eliminating identified failures on a certain priority. The set of failures that should be eliminated in this way is significantly overloaded by the subjective ratings of the FMEA team and can lead to a lack of success the required level of reliability and effectiveness of the manufacturing process, as well as the degree of utilization of the available budget. The considered problem becomes significantly more complicated when there is a large number of failures. In the literature, there are numerous predictive models that are based on a large amount of data.[14,15]

Motivation for this research comes from the fact that it is necessary to build up a sufficiently friendly model whose application can effectively determine the order of elimination of identified failures concerning their priority, the costs they respond to, and the available budget. In this way, the obtained solution is significantly less burdened by the subjective attitudes of the FMEA team, which leads to a greater improvement in the reliability and effectiveness of the manufacturing process.

In the literature, there are many industrial problems whose solution development is based on a genetic algorithm (GA), such as problems for assessing hazard systems,[16] shock absorber process parameters,[17] and site selection.[18] There are also many papers in which near-optimal solutions to various management problems in the manufacturing process are found by using variable neighborhood search (VNS), such as manufacturing scheduling problems,[19,20] manufacturing and assembly problem,[21,22] etc. In case, the FMEA report contains a small number of failures, using metaheuristic algorithms to solve the considered problem does not make sense. In cases of limited data samples, the selection of the optimal set of failures to be eliminated can be based on statistical classification (by analogy).[23]

In this research, the problem of choosing failures to eliminate is set as a knapsack problem. Many authors, solving this type of problem can be found by using GA,[24] and VNS.[25–27] Based on a detailed review of the relevant literature, it can be clearly concluded that there are no papers in which the solution to the considered problem is found in as exact way.

The objective is to evaluate and choose failures that have the greatest impact on the reliability and effectiveness of the manufacturing process in the automotive industry in uncertain conditions. This aim may be interpreted as (1) modeling of the existing uncertainties into (i) the relative importance of RFs and (ii) the costs incurred due to downtime failures are performed by using IT2TFNs, (2) the weight vector is obtained by IT2FAHP, (3) priority of failures is given by fuzzy RPN (FRPN), which is calculated as sum of weighted of RFs, (4) selection of failures is stated as problem combinatory optimization; The fitness function depends on FRPN and total cost; the limit is the financial resources that are committed to eliminating failures; a near-optimal solution can be obtained by applying different metaheuristic algorithms such as GA, and VNS. The obtained solution is significantly enabling the FMEA team to take the necessary actions in a shorter period of time to eliminate the marked failures, which achieves significantly better reliability and effectiveness of the manufacturing process.

The paper is organized in the following way: in Section 2 there is a problem statement. The methodology is presented in Section 3. Numerical results are presented in Section 4. Conclusion and discussion are given in Section 5.

Problem statement

This paper discusses the complex problem of operational management that exists in manufacturing companies that can be viewed as integrated systems. The solution to this problem can be found by applying the two-stage model, which is proposed in this paper and shown in Figure 1.

In the first part, the priority of identified failures is determined by using the FMEA framework, type 2 fuzzy sets, and IT2FAHP; in this way, the priority of identified failures is given. In the second part, a linear

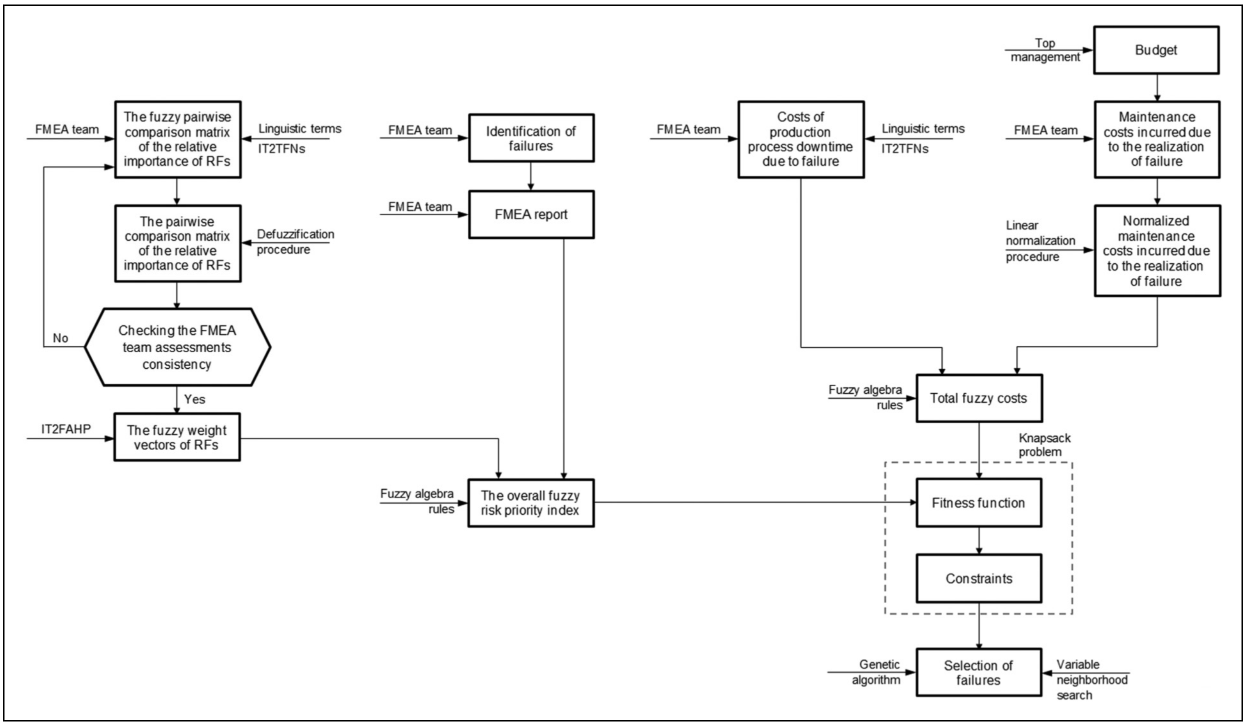

Figure 1. The proposed two-stage model.

optimization model was set up for choosing the set of failures that have the greatest impact on the reliability and effectiveness of the manufacturing process; best practice experiences show that the choice of failures that need to be eliminated to increase the reliability and effectiveness of the manufacturing process depends not only on their priority but also on the costs associated with them.

Respecting the above fact as well as that the number of failures that are most important for operational management is finite, it can be said that the considered problem belongs to the class of combinatorial optimization problems. The solution to such a problem can be found by applying various metaheuristic algorithms that efficiently search the space for solving the problem. The choice of a metaheuristic algorithm for solving a specific problem is not based on rules or recommendations but on intuition and experience. In this paper, GA and VNS were used to determine near-optimal solutions (optimal set of failures that should be eliminated by applying appropriate management actions) and a comparison and analysis of the obtained results were performed.

The following are assumptions underlying a model of the treated problem:

- FMEA team is defined for each considered company. These companies belong to the automotive industry and are part of various automotive supply chains, which operate in the Republic of Serbia. It should be emphasized that the mechanized technological level is predominantly represented in these companies. Only some parts of the manufacturing process are automated. The companies are approximate in size and belong to the group of small and medium companies. The structure of manufacturing workers of these companies is similar.
- Failures in the manufacturing process are identified by the FMEA team.
- Values of RFs are taken from the FMEA reports.
- The assessment of the relative importance of RFs was performed by FMEA teams by using the online interview method. They made the decision by consensus.
- FMEA team uses pre-defined linguistic terms which are modeled by IT2TFNs. The fuzzy weights vector is given by using IT2FAHP.
- The weighted RF values are calculated as product weights and RFs values by analogy[8,10,13]
- Priority of failures is determined according to fuzzy RPN which is calculated as the sum of the weighted RFs values by analogy[9] as in this manuscript.
- The realization of each identified failure leads to the generation of maintenance costs and costs of downtime of the manufacturing process, which to a greater or lesser extent affect the realization of both work tasks in the manufacturing process and other business processes. The total costs associated with each identified defect are calculated as the sum of maintenance costs and manufacturing process downtime costs.
- Maintenance cost values can be accurately determined by the maintenance manager and financial manager. They base their assessments on evidence data, at the same time respecting the projected changes in the financial market.
- The values of costs incurred due to downtime are estimated by the FMEA team based on its knowledge and experience. These costs are assessed by the FMEA team and modeled by IT2TFNs.

- As maintenance cost values are expressed in monetary units, it is necessary to map their value to the interval [0-1]. The linear normalization procedure was used in this research.[28]
- In practice, the FMEA team bases its decision on the selection of failures to be eliminated on two points: that the priority is as high as possible and that the total costs are as low as possible. Hence, in this research, the fitness function is defined as the quotient of the fuzzy RPN and the total costs.
- The constraint is related to the budget available to the FMEA team.

In order to better understand the model, a notation was introduced, which is presented below:

The choice of linguistic expression for describing the relative importance of rfs and determining of weights vector

Respecting the size and complexity of the problem, three pre-defined linguistic expressions are defined to describe the relative importance of RFs. These linguistic expressions are modeled by IT2TFNs and Table 1:

Table 1. Pre-defined linguistic expressions used to describe the relative importance of RFs.

Low importance (W1)	((1, 1, 5; 1), (1, 1, 4; 0.7))
Moderate importance (W2)	((1, 3, 5; 1), (2, 3, 4; 0.7))
Very high importance (W3)	((1, 5, 5; 1), (2, 5, 5; 0.7))

In most of the analyzed papers, the authors define the domain of IT2TFNs on a common measurement scale.[29] Some authors[2,30] use a scale [1-10]. In this manuscript, the authors propose a measurement scale defined in the interval [1-5]. A value of 1 or 5 means that RF k has the equal or extreme relative importance of RF k in relation to RF k', $k, k' = 1, .., K$.

Since the overlaps from one IT2TFN to the others are very high. It obviously indicates that there is a lack of FMEA team knowledge about the degree of importance of RFs or a lack of sufficient partitioning. The proposed values represent the initial draft assessed by the FMEA team's opinion on the automotive industry in Serbia.

The consistency check is performed by using the Eigen vector method[29] concerning the pair-wise comparisons matrix to determine if there were errors during evaluation or not. Element values of the pair-wise comparison matrix should be obtained by using different defuzzification procedures. The defuzzification procedure by Kahraman et al.[31] is most used in the literature, as well as in this research. The type 2 fuzzy weights vectors are given by using a fuzzy geometric operator, by analogy to Buckley.[5] The weights of RFs are described by IT2TFNs.

Choice linguistic expressions for describing downtime costs

Reducing business efficiency due to delays in the manufacturing process induces certain costs that are difficult to determine precisely. The FMEA team can describe these costs well enough by using pre-defined linguistic expressions. They usually base their assessments on experience.

In this research, the seven-point scale is used for describing costs that arise due to manufacturing downtime which are modeled by IT2TF as follows in Table 2:

The domains of IT2FNs are defined on the measurement scale defined into interval [0-1]. A value of 0 or 1 means that the costs incurred due to downtime have a negligible, i.e., extremely high value, respectively.

The proposed mathematical model

The proposed algorithm is presented through the following steps:

Step 1: The fuzzy pair-wise comparison matrix of the relative importance of RFs is stated:

$$[\tilde{\tilde{W}}_{kk'}]_{KxK}$$

where:

$$\tilde{\tilde{W}}_{kk'} = ((a^U_{1kk'}, a^U_{2kk'}, a^U_{3kk'}; 1)(a^L_{1kk'}, a^L_{2kk'}, a^L_{3kk'}; \alpha))$$

Step 2: Transform the fuzzy pair-wise comparison matrix to a pair-wise comparison matrix by using the defuzzification procedure[31]:

$$[W_{kk'}]_{KxK}$$

Table 2. Pre-defined linguistic expressions used to describe describing costs that arise due to manufacturing downtime.

Almost negligible costs (C1)	((0.10, 0.10, 0.25; 1), (0.10, 0.10, 0.2; 0.85))
Very low costs (C2)	((0.15, 0.25, 0.35; 1), (0.2, 0.25, 0.30; 0.85))
Fairly low moderate costs (C3)	((0.25, 0.40, 0.55; 1), (0.30, 0.35, 0.50; 0.85))
Moderate costs value (C4)	((0.40, 0.55, 0.70; 1), (0.45, 0.55, 0.65; 0.85))
Fairly high moderate costs (C5)	((0.55, 0.70, 0.85; 1), (0.60, 0.70, 0.80; 0.85))
Very high costs (C6)	((0.75, 0.85, 0.95; 1), (0.80, 0.85, 0.90; 0.85))
Extremely high costs (C7)	((0.85, 1, 1; 1), (0.90, 1, 1; 0.85))

Where:

$$W_{kk'} = DTriT\ \tilde{\tilde{W}}_{kk'} \times \frac{1}{2}\left\{\frac{(\mathrm{a}^{\mathrm{U}}_{3kk'} - \mathrm{a}^{\mathrm{U}}_{1kk'}) + (\mathrm{a}^{\mathrm{U}}_{2kk'} - \mathrm{a}^{\mathrm{U}}_{1kk'})}{3} + \mathrm{a}^{\mathrm{U}}_{1kk'} + \alpha \cdot \left[\frac{(\mathrm{a}^{\mathrm{L}}_{3kk'} - \mathrm{a}^{\mathrm{L}}_{1kk'}) + (\mathrm{a}^{\mathrm{L}}_{2kk'} - \mathrm{a}^{\mathrm{L}}_{1kk'})}{3} + \mathrm{a}^{\mathrm{L}}_{1kk'}\right]\right\}$$

Using the Eigenvector method[29] the consistency of the estimates of DMs is checked.

Step 3: The weights vector, $[\tilde{\tilde{\omega}}_k]_{1xK}$ is given by using the procedure[31]:

$$\tilde{\tilde{\omega}}_k = \left(\begin{array}{l} \left(\frac{\sqrt[K]{\prod_{k'=1,..,K} a^U_{1kk'}}}{\sum_{k=1,..,K}\sqrt[K]{\prod_{k'=1,..,K} a^U_{3kk'}}}, \frac{\sqrt[K]{\prod_{k'=1,..,K} a^U_{2kk'}}}{\sum_{k=1,..,K}\sqrt[K]{\prod_{k'=1,..,K} a^U_{2kk'}}}, \frac{\sqrt[K]{\prod_{k'=1,..,K} a^U_{3kk'}}}{\sum_{k=1,..,K}\sqrt[K]{\prod_{k'=1,..,K} a^U_{1kk'}}}; 1\right) \\ \left(\frac{\sqrt[K]{\prod_{k'=1,..,K} a^L_{1kk'}}}{\sum_{k=1,..,K}\sqrt[K]{\prod_{k'=1,..,K} a^L_{3kk'}}}, \frac{\sqrt[K]{\prod_{k'=1,..,K} a^L_{2kk'}}}{\sum_{k=1,..,K}\sqrt[K]{\prod_{k'=1,..,K} a^L_{2kk'}}}, \frac{\sqrt[K]{\prod_{k'=1,..,K} a^L_{3kk'}}}{\sum_{k=1,..,K}\sqrt[K]{\prod_{k'=1,..,K} a^L_{1kk'}}}; \alpha\right) \end{array}\right)$$

and

$$\tilde{\tilde{\omega}}_k = ((b^U_{1k}, b^U_{2k}, b^U_{3k}; 1)(b^L_{1k}, b^L_{2k}, b^L_{3k}; \alpha))$$

Step 4: The overall fuzzy risk priority index, $\tilde{\tilde{p}}_t$:

$$\tilde{\tilde{p}}_t = \sum_{k=1,..,K} v_{tk} \cdot \tilde{\tilde{\omega}}_k$$

and

$$\tilde{\tilde{p}}_t = ((d^U_{1t}, d^U_{2t}, d^U_{3t}; 1)(d^L_{1t}, d^L_{2t}, d^L_{3t}; \alpha))$$

Step 5: Each failure is accompanied by maintenance costs, c_{1t}., and downtime of manufacturing process costs $\tilde{\tilde{c}}_{2t}$., $t = 1, \ldots, T$.

Step 6: The total costs due to the realization of failure are determined *t*, $\tilde{\tilde{c}}_t$, $t = 1, .., T$:

$$\tilde{\tilde{c}}_t = r_{1t} + \tilde{\tilde{c}}_{2t}$$

Where:

$$r_{1t} = \frac{c_{1t}}{\sum_{t=1,..,T} c_{1t}}$$

and

$$\tilde{\tilde{c}}_t = ((g^U_{1t}, g^U_{2t}, g^U_{3t}; 1)(g^L_{1t}, g^L_{2t}, g^L_{3t}; \beta))$$

Step 7: The optimization mode is set:

The fitness function

$$\max_{j=1,..,J}\ \left(defuzz \sum \frac{\tilde{\tilde{p}}_t}{\tilde{\tilde{c}}_t}\right)$$

$$\max_{j=1,..,J}\ defuzz \sum\left(\left(\frac{d^U_{1t}}{g^U_{3t}}, \frac{d^U_{2t}}{g^U_{2t}}, \frac{d^U_{3t}}{g^U_{1t}};\ \min(1, 1)\right), \left(\frac{d^L_{1t}}{g^L_{3t}}, \frac{d^L_{2t}}{g^L_{2t}}, \frac{d^L_{3t}}{g^L_{1t}};\ \min(\alpha, \beta)\right)\right)$$

Objective

$$\sum_{j=1,..,J} c_{1j} \le C$$

The model contains a linear fitness function that corresponds to the maximization of the relationship between total priority and total cost failure for the considered time period under the analysis. In the considered problem, the time period is one year. The model contains one linear constraint expressing the total maintenance costs for the selected set of failures.

In the next section, this model is solved by using two metaheuristic algorithms: GA and VNS. The verification of the efficiency of the used metaheuristic elements was performed by testing on FMEA reports that have a different number of failures. Time, as well as the number of iterations of obtaining a near-optimal solution, are the criteria on the basis of which a metaheuristic algorithm can be proposed, which is the most applicable for solving the considered problem.

Solution methods

In this section, two meta-heuristics are presented to obtain good solutions for different problem instances. Respecting to the nature of considered problem, it can be said that we consider problems with medium instances. For this problem, GA is implemented in Section 4.1 and VNS in Section 4.2.

The assumptions introduced in the VNS are: (1) that the systematic application of several local searches can be found the local optimum, which preserves the best current solution, and (2) by defining neighboring solutions it will expectantly cover the global optimum.

Genetic algorithm

The basic GA developed by Holland[32] was inspired by evolutionary biology such as inheritance, mutation, selection, which are evolutionary algorithms that are inspired by and crossover.[33] The main difference between classical, isolated-based optimization algorithms and GA are[34]: (i) a classical algorithm produces one solution at each replication and the suite of solution approaches optimal solutions and (ii) a GA generates a population of solution at each replication and the best solution in the population accosts an optimal solution. The basic steps of a GA are the initialization, the evaluation, the selection, the crossover, the mutation, and the repetition.

In this manuscript, applied GA is performed under the following statements: (i) The probability of parental selection is defined as proportional to fitness, (ii) The elitism parameter is set to 0.05%, (iii) Chromosomes are encoded by a binary record of length equal to the

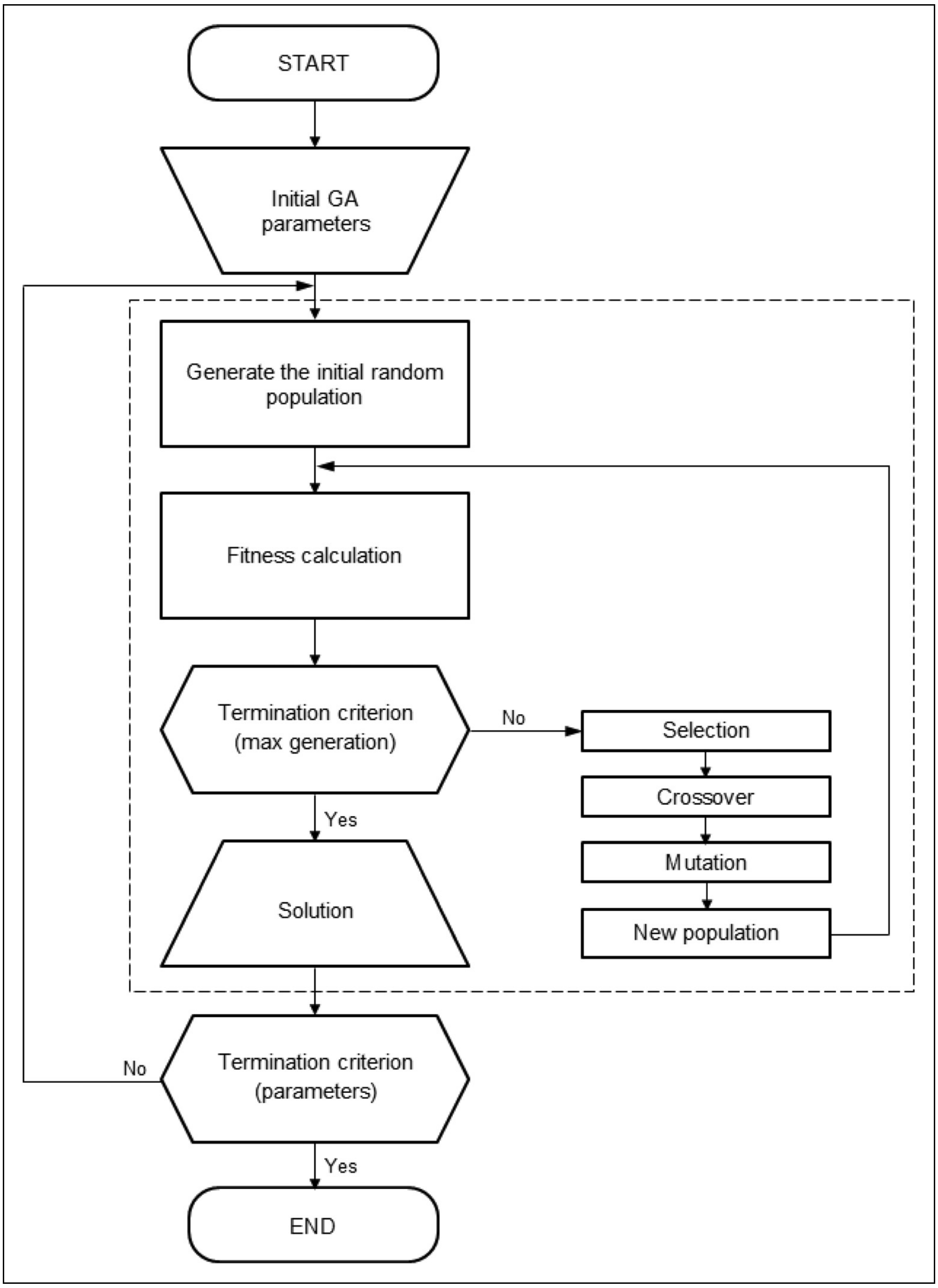

Figure 2. Ga algorithm.

number elements, (iv) A uniform crossing operator with one fixed point was used, (v) GA parameters: number of population units 100, number of iterations limited to 1000000, as is shown in Figure 2.

A new function in the implementation of GA has been introduced, which enables automated adaptive program control of crossover and mutation parameters for each individual data set, which is a form of hyperheuristics, such as:

GA is implemented in the C# (C Sharp) programming language Table 3.

Variable neighborhood search

Solving of many global optimization problems is based on VNS.[35] VNS is a metaheuristic algorithm, which systematically varies the neighborhood structure to constantly search for new neighborhood solutions, where to derive a feasible global optimal solution.[21] They authors emphasize that there are different ways to make an order of neighborhood structure. In this research, we defined the structures of the neighborhood using the concept of inserting and ejecting elements from the knapsack as follows (Figure 3):

(1) Neighborhood 1: inserting 1 element and ejecting 1, (2) Neighborhood 2: inserting 2 elements and ejecting 2, (3) Neighborhood 3: inserting 3 elements and ejecting 3 elements, (4) Neighborhood 4: ejecting 2 elements, (5) Neighborhood 5: inserting 2 elements, Neighborhood (6) Neighborhood 6: ejecting 3 elements, (7) Neighborhood 7: inserting 3 elements.

When determining the order of the neighborhoods, two factors were taken into account that describes the difference between a current solution and a solution from a particular neighborhood: Change in the number of elements in the knapsack - "B" and Hamming distance of solution presentation - "H". This is expressed in defined neighborhoods as follows B, H:

Neighborhood 1 - 0.2; Neighborhood 2 - 0.4; Neighborhood 3 - 0.6; Neighborhood 4 - 2.2; Neighborhood 5 - 2.2; Neighborhood 6 - 3.3; and Neighborhood 7 - 3.3.

Basic VNS (BVNS) method which combines deterministic and stochastic changes - the best improvement ascent method with randomization, was applied to find a set of failures that have the greatest impact on the reliability and effectiveness of the manufacturing process with the following properties: (1) the initial feasible solution is constructed randomly, (2) the initial feasible solution is achieved by applied best improvement local search; the obtained solution is denoted as the best solution, (3) in the phase of shaking, the permissible solution in the current neighborhood is chosen in a random way. By applying the best improvement local search, the current solution found has been improved. If the improved solution from the current neighborhood is better than the currently best solution, there is a new best solution and the neighborhood counter is reset. If not, move on to the next neighborhood and repeat the last step. The termination criterion is a predetermined time period. Local search in our implementation is performed by searching all solutions at Hamming distance 1 from the current solution.

Table 3. Used GA parameters.

Sample size	Crossover parameter	Mutation parameter
25	0.90	0.10
50	0.90	0.05
87	0.95	0.05
93	0.95	0.05
146	0.90	0.02

Numerical results

The near-optimal solution (Step 6 of the proposed Algorithm) is obtained by GA and VNS. For all five FMEA reports, optimal solutions were found using both algorithms in a reasonable time on a Pentium PC (Intel(R) Core(TM) i5-9600KF CPU @ 3.70GHz - 16.0 GB RAM). The obtained results are presented in Table 4.

Discussion

The set of failures considered in FMEA reports in the automotive industry can be observed as a small sample size problem. Determining the optimal set of failures that must be eliminated, in a broader sense, can be stated as a classification problem. In the literature, may be found numerous methods for classification with small data size,[23] can be used to obtain sufficiently reliable results. It is known that these methods can be applied if it is possible to estimate the probability distribution of the model parameters.

In this research, there is not enough evidence on the basis of which the probability distribution of the relative importance of RFs and downtime of manufacturing process costs would be estimated. Therefore, determining the optimal set of failures is based on the application of GA and VNS. This significantly shortens the application time of the FMEA analysis and increases the efficiency of the FMEA team. In this way, the reliability and effectiveness of the manufacturing process increase, which further leads to the realization of operational aims.

Based on the results shown in Table 4, it is clear that the application of both methods gives the same results. From the engineering aspect, the obtained solution is stable. It should be noted that for the problem discussed in this paper, the application of VNS for a shorter time can be obtained near the optimal solution, which gives an advantage to this method over GA.

By analyzing the FMEA report and the results shown in Table 4, it can be clearly concluded that the optimal solution at the level of each company is a set of failures caused by human factors. Respecting this fact, the

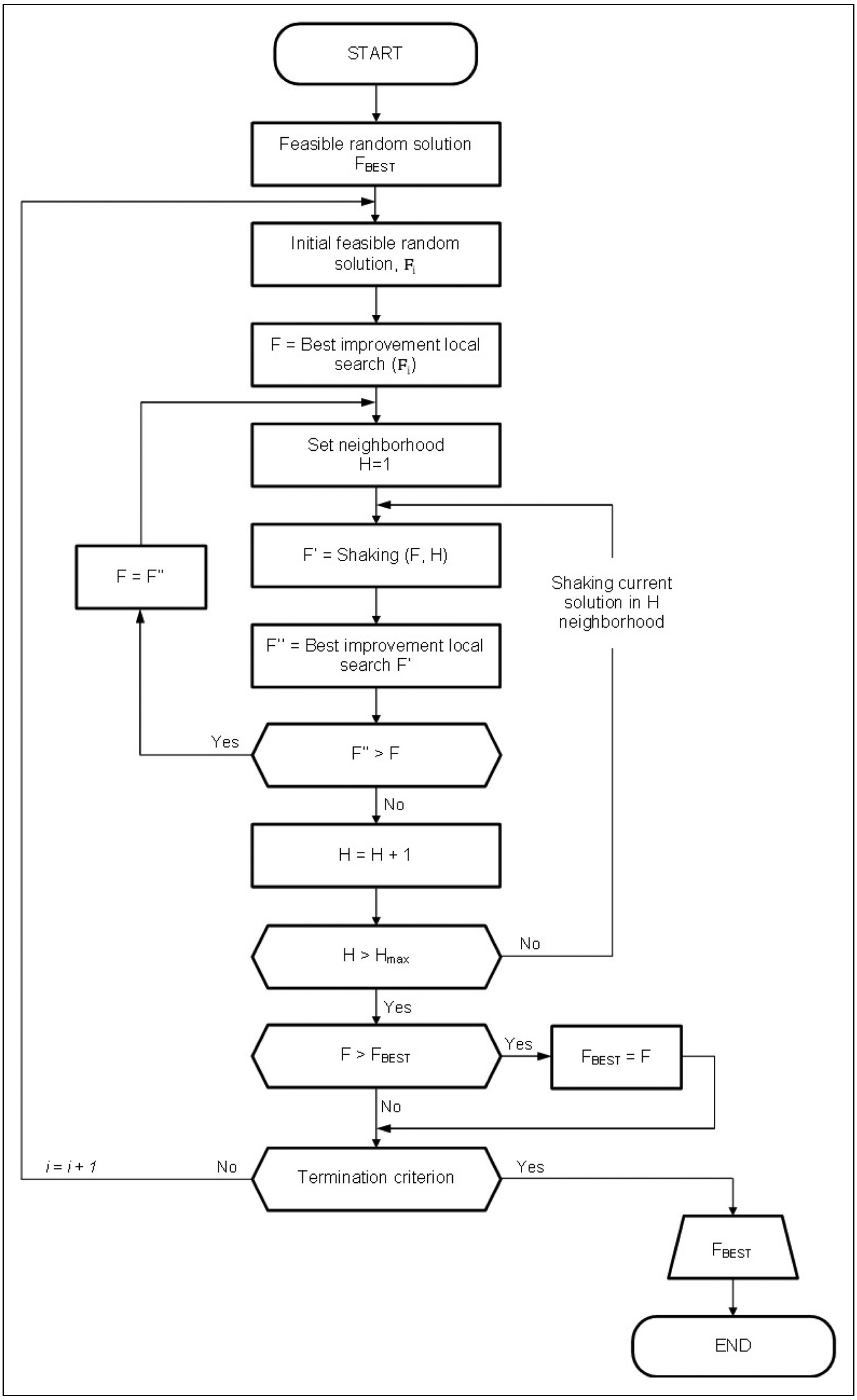

Figure 3. VNS algorithm.

FMEA team should: (i) prescribe a procedure for controlling the work of workers in the workplace to prevent the occurrence of selected failures, (ii) introduce visual management methods, such as the Poka-Yoke system, (iii) propose the various employe training courses, and (iv) introduce source failure control, etc.

Table 4. The sets of failures that have the highest priority at the level of each analyzed FMEA report.

Sample size	GA Optimal solution	GA Number of iterations	GA Time	GA Fitness function value	VNS Optimal solution	VNS Number of iterations	VNS Time	VNS Fitness function value
25	2,3,4,5,7,8,9,10,11,12,13,14,15,18,22,23,24	386	1.346	281278	2,3,4,5,7,8,9,10,11,12,13,14,15,18,22,23,24	206	1.194	281278
50	4,5,6,7,8,10,11,13,14,15,16,17,18,19,22,24,26,29,30,31, 32,33,34,35,36,39,40,41,42,45,46,47,48,49,50	18663	52.144	525150	4,5,6,7,8,10,11,13,14,15,16,17,18,19,22,24,26,29,30,31, 32,33,34,35,36,39,40,41,42,45,46,47,48,49,50	75	0.646	525150
87	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,21,22,23,24, 25,26,29,30,31,32,37,38,39,40,41,42,43,44,45,46,49, 51,52,53,54,55,56,57,58,61,62,64,65,66,69,70,71,72, 73,74,75,76,77,78,81,84,85,86	66913	265.151	836380	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,21,22,23,24, 25,26,29,30,31,32,37,38,39,40,41,42,43,44,45,46,49, 51,52,53,54,55,56,57,58,61,62,64,65,66,69,70,71,72, 73,74,75,76,77,78,81,84,85,86	400	3.406	836380
92	1,4,9,10,12,14,15,16,17,18,22,23,25,26,27,28,29,30,31, 32,34,36,37,38,39,40,41,42,43,44,45,46,48,49,50,51, 52,54,55,56,57,59,60,62,65,66,68,69,70,72,73,74,76, 77,80,82,83,84,85,86,87,88,89,90,91,92	7697	108.019	1459638	1,4,9,10,12,14,15,16,17,18,22,23,25,26,27,28,29,30,31, 32,34,36,37,38,39,40,41,42,43,44,45,46,48,49,50,51, 52,54,55,56,57,59,60,62,65,66,68,69,70,72,73,74,76, 77,80,82,83,84,85,86,87,88,89,90,91,92	446	4.327	1459638
146	1,2,3,4,5,6,7,8,9,13,14,15,16,18,19,20,22,23,24,25,26, 27,28,29,31,32,34,37,39,40,42,43,46,47,48,49,50,51, 52,53,54,55,56,57,58,59,60,61,62,63,64,66,67,68,69, 70,71,72,73,74,77,78,79,80,81,82,83,84,85,86,87,88, 89,90,93,98,99,100,101,102,105,106,111,112,118, 119,120,121,122,123,124,125,139,141,142,143,144, 145,146	244727	1446.337	1713944	1,2,3,4,5,6,7,8,9,13,14,15,16,18,19,20,22,23,24,25,26, 27,28,29,31,32,34,37,39,40,42,43,46,47,48,49,50,51, 52,53,54,55,56,57,58,59,60,61,62,63,64,66,67,68,69, 70,71,72,73,74,77,78,79,80,81,82,83,84,85,86,87,88, 89,90,93,98,99,100,101,102,105,106,111,112,118, 119,120,121,122,123,124,125,139,141,142,143,144, 145,146	4371	102.612	1713944

Conclusion

Companies in the automotive industry that are organized as a global supply chain have a strong influence on the development of the national economies of many countries. The competitiveness and sustainability of these companies can be achieved, among other things, by increasing the reliability and effectiveness of the manufacturing process.

The main contribution of the research may be structured through the following components: (1) improving FMEA, and (2) determining the failures that need to be eliminated.

According to Liu et al.[6] some of the shortcomings of conventional FMEA analysis are: (i) the assessments of the FMEA team are based on using precise numbers; in this article, the relative importance of RFs is expressed by linguistic terms which are modeled by IT2TFNs and (ii) equal relative importance of criteria. In this paper, the relative importance of risk factors is set using a pairwise comparison matrix with IT2TFNs. The weights vector is obtained by using a fuzzy geometric mean.

In automotive practice, determining the set of failures to be eliminated is based on the assessment of the FMEA team. They base their estimates on the priority of failures (determined according to RPN values), knowledge, experience, and available budget. In order to increase the efficiency of GA in solving the observed data sets, an additional logical layer in the implementation that programmatically managed the GA parameters and modified them according to the results of the algorithm is introduced. Taking into account the nature of the KP (knapsack problem) and the fact that best-improvement local search in the proposed VNS variant quickly leads to a solution with a constraint limit value, neighborhood structures that combine solution distance with changing a number of solution elements in both directions were used. In this way, we additionally avoided premature jams in local optimums, which was especially seen through the improvement of results by shifting to neighborhoods 4 and 6. The presented results show the success of the proposed VNS algorithm in solving the presented data sets.

The model is flexible enough that changes in the type and number of failures, as well as the relative importance of RFs which depends on the place of appearances of failures, for example,[36] as well as the type of industry, for example,[37] can be easily incorporated into the model.

The practical contribution of this paper can be seen as the development of two algorithms that helps DMs to have less subjectivity in making these decisions. Using a user-friendly algorithm increases the accuracy of the FMEA team's decision, which implies increasing the reliability and effectiveness of the production process. The main limitation of the proposed model is the high subjectivity of DMs in assessing existing uncertainties.

Future research includes: (1) failure estimates respecting multiple risk factors, such as product importance[38] and severity in terms of cost,[39–41] (2) modification of the proposed KP problem, which implies the introduction of constrains and (3) the application of the proposed model in different industrial domains.

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Author contributions

Nikola Komatina: Collection and processing of input data, development of the proposed model, analysis of available literature, and technical processing and correspondence. Danijela Tadić: Development of the proposed model, analysis of available literature, and analysis of the obtained results. Goran Đurić: Application of metaheuristic approaches and definition of their application algorithms, and development of the proposed model. Aleksandar Aleksić: Collection and processing of input data, analysis of the obtained results.

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Appendix

Notation

T	Total number of identified failures
t	Index of failure
K	Total number of RFs
k	Index of RF
$\tilde{W}_{kk'}$	IT2TFN describing the relative importance of RF, k over RF k' ; $k, k' = 1, .., K;\ k \neq k'$
$\tilde{\tilde{\omega}}_k$	IT2TFN describing fuzzy weight of RF k, $k = 1, .., K$
v_{tk}	Crisp values of RF k, $k = 1, .., K$ for failure t, $t = 1, \dots, T$
$\tilde{\tilde{p}}_t$	IT2TFN describing the overall fuzzy risk priority index
c_{1t}	Maintenance costs incurred due to the realization of failure t, $t = 1, \dots, T$
r_{1t}	Normalized value of maintenance costs incurred due to the realization of failure t, $t = 1, \dots, T$
$\tilde{\tilde{c}}_{2t}$	IT2TFN that correspond to costs of manufacturing process downtime due to failure t, $t = 1, \dots, T$
$\tilde{\tilde{c}}_t$	Total costs incurred due to the realization of failure t, $t = 1, \dots, T$
C	Total funds allocated to the activities of the FMEA team