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A SOFTWARE MODULE FOR MULTI-CRITERIA SUPPLIERS' SELECTION WITH RESPECT TO THE SPARE PARTS LOGISTIC

Summary. Reliability of vehicles is characterized not only by the quality of production but also by the quality of subsequent maintenance. In this paper, we consider the possible spare parts logistics risks, as they have a huge influence on vehicles' maintenance. One of the widespread methods to analyze the reliability of complex systems is Fault Tree Analysis (FTA). To identify and systematize all possible risks in spare parts logistics, we have built the Problem Tree. For managing identified risks, we propose a conceptual scheme of an intelligent system. In the framework of this paper, we describe one of the modules that make up this intelligent system. The proposed software module will help to choose the spare parts' suppliers taking into account their reliability from the logistical point of view. It was tested with the use of real data from an automotive manufacturer.

1. INTRODUCTION

Globalization of automotive markets as well as the high competition are forcing automotive manufacturers to find ways to reduce costs, increase efficiency and improve the quality of their finished products and services [1]. One of the ways to increase the quality and efficiency is the transition to a circular economy, which means the development of eco-friendly technical and technological systems. According to the research of the international company, Persistence Market Research [2], their introduction into the automotive industry will create an opportunity to reduce the consumption of raw materials by 98%; to save 83% of energy; decrease the cost of finished products up to 40%; and decrease carbon dioxide emissions up to 87%. A circular economy is formed by closed-loop supply chains, i.e. to deliver automotive spare parts from suppliers to the dealer and service centers (DSCs) and to return the empty packaging as well as the faulty spare parts back to its suppliers (Fig. 1). A circular economy is currently a popular concept that requires fundamentally new logistics approaches. However, before adopting a new concept, manufacturers need to examine existing supply chains to identify areas that can be improved, as well as assess the risks.

In the transition to closed supply chains in the frame of a circular economy, the corporate governance system should include mechanisms for automatic risk identification, assessment and decision-making. To do this, it is necessary to consider all possible risks that may arise at each stage of the life cycle of a vehicle. The efficiency of vehicles' operation depends not only on their design and manufacturing but also largely on their maintenance during the operation phase, which is closely related to the logistics of spare parts. Thus, an intelligent system to manage spare parts logistics, which takes into account technical, technological, operational and environmental risks, has to be developed.

Intelligent management systems, which have mechanisms for monitoring the current state of the system, fast and timely transmission of information and qualitative data analysis for subsequent planning and prediction, allow the development of an efficient risk management mechanism.

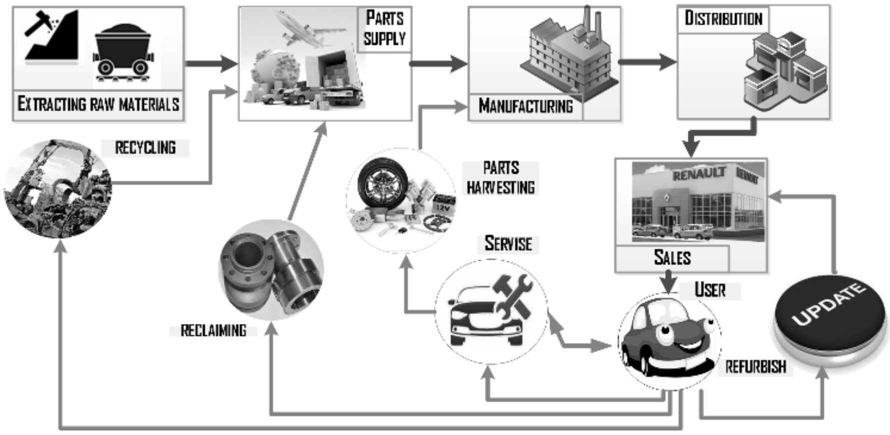


Fig. 1. Closed-loop supply chain in a circular economy

The authors of the study [3] have proved that intelligent systems based on problem analysis methods (in their case, the Root Cause Analysis method was used) are an effective tool for assessing the probability of failure of complex technical systems. In this respect, the third section of this article is devoted to the developed software module of supplier selection to improve the reliability of spare parts logistics based on one of the problem analysis methods: Problem Tree Analysis.

2. RELATED RESEARCHES AND BACKGROUND

2.1. Risk analysis methods

Risks can be assessed by two parameters: the probability of the risk situation occurring and the severity of its consequences. Considering risks from the managerial viewpoint, one has to take into account that risks arise in all spheres and they cannot be completely eliminated, but they can be managed. According to the PMI standard [4], risk management includes the processes related to identifying, analyzing and responding to project risks.

When analyzing risks, the following assumptions are possible [5]: losses from risk are independent of each other; loss in one activity area does not necessarily increase the loss probability in another (with the exception of force majeure circumstances); and the maximum possible damage should not exceed the participants' financial capabilities. Risk management aims to achieve the following main objectives:

- to form for the decision maker a risks' holistic vision, which threaten the managed system interests;
- to rank risks by the degree of their influence on the organization activities and to identify the most critical among them;
- to compare alternative versions of projects and technologies;
- to create databases and knowledge bases for expert systems to adopt technical and other solutions; and
- to justify risk mitigation measures.

The risk zone is defined by the general zone of market losses within which losses do not exceed the limit value of the established level of risk. Risk analysis can be divided into two complementary types: qualitative and quantitative. Qualitative analysis is carried out using the method of expert assessments.

A quantitative risk analysis is needed to assess how the most significant risk factors can affect performance. Qualitative analysis is aimed at identifying factors, areas and types of risks. Quantitative risk analysis should make it possible to quantify the size of individual risks and the risk of the producer. To carry out a quantitative analysis, a risk map (or risk matrix) can be prepared, which allows determining the most significant of them. Quantitative risk assessment is a crucial step in the safety analysis of process systems. The advancement of modern process systems has made a large volume of process data and information available for process safety analysis. Quantitative analysis of the identified risks is carried out by sensitivity analysis. Sensitivity analysis can be performed using specialized software packages.

There are a lot of traditional risk assessment methods (the basic ones), for example, risk radar [6], risk chart [7], risk map (risk matrix) [8], SWOT-analysis [9], etc. For the reliability analysis of complex systems, Fault Tree Analysis (FTA) [10, 11], Failure Modes and Effects Analysis (FMEA) [12, 13] and Monte Carlo Simulation (MCS) [14] are applicable. In paper [15], it was proved that with the help of hybrid approaches it is possible to more accurately identify functional limitations and factors contributing to the accidents occurrence. Researchers use various combinations of different methods [16, 17] because for different problems under consideration, different approaches are more efficient. Authors of the research [18] propose a methodology for mapping FTA into an Artificial Neural Network (ANN) to support the convenient and practical application of ANN in risk assessment.

2.2. Risks over the vehicle's life cycle stages

There are several categories of risks in automotive logistics systems. In the transition to new logistical approaches, there are several challenges, and manufacturers sometimes delegate their logistics management to a third-party logistics provider. Such outsourcing can also lead to some risks. These are considered in [19]. The authors divide the possible risks into the following categories: financial (customer satisfaction, contract and penalties, backorders and re-work) and operational (resource allocation, workforce performance, currency exchange). The paper [20] deals with automotive supply chain risks management and includes such types of risks as Supply Risk (poor quality of raw materials, raw parts scarcity, decline in business relations with suppliers), Process Risk (product design risk, lack of skilled operators, machine breakdown), Financial Risk (cash flow disruptions, low rate of return, high inventory cost) and Demand Risk (shifting demand across time, shifting demand across market, shifting demand across product). Authors of [21] have classified possible automotive spare parts supply risks into 6 categories: market risk, liquidity risk, volume/capacity/demand risk, counterparty risk, operating risk and risk interrelations.

After studying all the above-mentioned and some other research works, we have drawn the conclusion that risks in the automotive industry have to be classified at all lifecycle stages of vehicles, including the development of terms of reference, design, manufacture and disposal. Classification of the risks that we propose is presented in Fig. 2.

It is important to understand that all risk types are related to each other and the emergence of one risk situation can have a negative impact on the activities of related subsystems. For example, a decrease in vehicles' sales volume will negatively affect the need for spare parts and services, which, in turn, will lead to underutilization of working capacities, personnel, and equipment. *Production risk* is caused by malfunctions in the functioning of the production system. This is a violation in the operation of any of the DSS subsystems: a decrease in sales volumes, volumes of services, a violation in the supply chain, etc.

Technological risk is due to an improperly chosen technology of maintenance and repair. *Investment risk* is associated with the costs of new projects, for example, with the expansion of DSN. This risk characterizes the likelihood or amount of possible investment losses in the creation, equipping and maintenance of additional work positions when underutilizing production capacity or loss of profit from loss of customers due to deficient production opportunities. *Innovation risk* is the probability of a loss of investment if, contrary to expectations, new production or new services are not in demand on the market. *Criminal risk* is associated with risk situations that affect the health and life of a person: the risk of premature vehicle breakdown during its operation, and the risk associated with production technology violations while providing services. *Financial risk* is associated with the specifics of investing money in various projects.

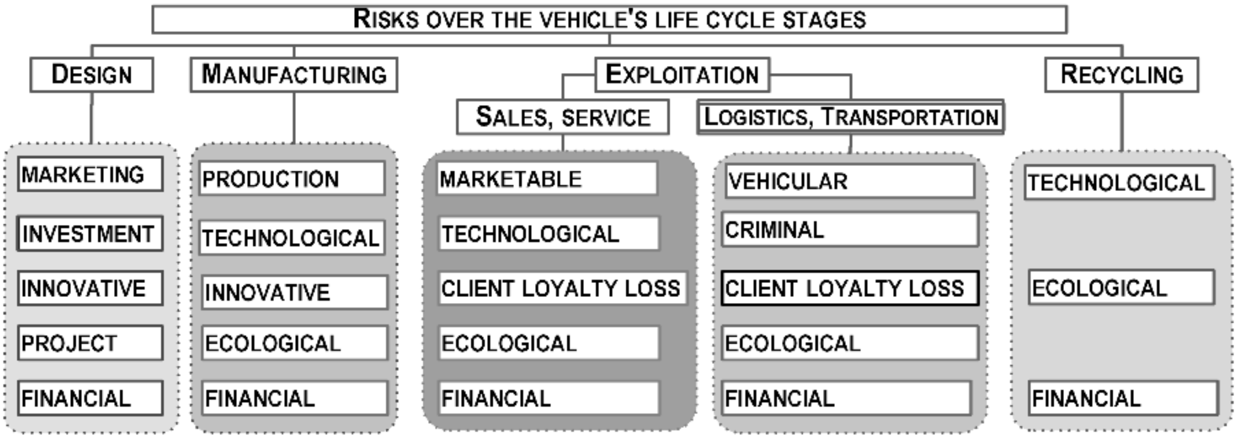


Fig. 2. Proposed classification of automotive industry risks

Technical risk determines the production organization degree, the possibility of carrying out preventive measures (regularity preventive check of equipment, security measures) and equipment repair by the company's own capabilities. This risks type belongs to the group of internal risks to manufacturing system ones because these risks can be directly influenced by the manufacturer, and their occurrence, as a rule, depends on the production activity itself. Technical risks are as follows:

- probability of losses due to negative research results;
- probability of losses due to failure to reach the planned technical parameters when designing;
- probability of losses due to low production technological capabilities, which does not allow the application of the results of new developments;
- likelihood of loss due to side effects or problems with delayed manifestation when using new technologies and products; and
- probability of losses due to failures and equipment breakdown, etc.

In our opinion, the *exploitation risks* are inseparable from the stage of technical operation, which means maintaining the vehicle, as a technical system, in good condition. The effectiveness of the technical systems operation depends to a large extent on the reliability of both the individual devices in the systems and the elements that ensure interaction between these devices. The parts and units limiting the reliability of the vehicle's aggregates are those that fail at least 50% of the total number of failures, and the costs for eliminating these failures (for spare parts and replacement work) are not less than 70% of the total cost. Also, to predict the possibility of exploitation risk, failure statistics must be considered. At the same time, it is necessary to take into account that the reliability of each spare part is determined not only by the reliability of the spare parts themselves but also by the reliability of the supply itself, i.e. compliance with its conditions and the speed of the organization of logistics processes. This is why the *risk of client loyalty loss*, which arises when the customer is not satisfied with the service quality, can be caused both by product's low quality and by the problems related to logistics and transportation [22]. In [23], authors call such risks social risks and state that these risks can lead to claims for damages and finally to decreases in turnover and profits.

3. RESULTS AND DISCUSSIONS

3.1. The Conceptual Scheme of an Intelligent System

There is no efficient technical systems' failure analysis method because its efficiency depends on the problem under consideration. Authors of [24] assert that FMEA is easily affected by human factors, MCS takes too much simulation time, which affects its operational efficiency, and FTA is mostly suitable for technical risks analysis. We suggest using one of the problem analysis methods, Problem Tree Analysis, as the basis for an intelligent spare parts logistics management system. We have chosen this method because it can be used for the following: (1) classification and systematization of the main problems that may arise while organizing logistics processes (including the supplier selection problem, building supply chains within the dealer-service network and organizing the delivery and storage of spare parts) and (2) identifying the possible consequences of these problems.

Since we have determined that the quality of vehicle maintenance depends not only on the reliability of spare parts but also on spare parts logistics, we have built the Problems Tree to identify and systematize all possible risks in spare parts logistics (Fig. 3).

There are two main problems that can negatively affect the quality of service in DSC: unreliable spare parts and unreliable spare parts supply logistics. Reliability of a spare part can be estimated by the duration of its failure-free operation. To determine the numerical value of this characteristic, it is necessary to carry out processing of the vehicle's units and aggregate failure statistics. Unreliability of spare parts logistics can be characterized by delivery delays and by the total or partial absence of the spare parts kit (the risks of cargo loss and its damage on route). Delivery delays can be caused by (1) no optimal managerial decisions (choice of the optimal route and traffic schedule, choice of transport mode, choice of the supplier, the number of overload nodes and the change of transport mode in logistic chain, the need to re-arrange the consignment in overload nodes), (2) delays along the route related to vehicle malfunction, road accidents, sudden degradation of driver's health or delays in loading/unloading bays, or (3) unexpected, huge and infrequent force majeure situations.

In general, authors of the paper [25] classify possible risks into two broad groups, namely, fluctuation (small and frequent variations such as price changes, currency exchange, transportation delays that can be improved by operational-level decisions) and disruption (unexpected, huge and infrequent variations such as extreme weather conditions, sanctions and wars that should be considered in strategic-level decisions dealing with the selection of suppliers and other partners). To manage both operational- and strategic-level types of risks, intelligent systems have to be developed.

The intelligent system to manage the spare parts logistics is the basis for interaction between production and service systems in the implementation of the principles of circular economics and green technologies. To prevent problems described in the Problems Tree (Fig. 3), the proposed intelligent system must include the following:

- module for data collection and storage;
- module for data analysis;
- module to forecast the need for spare parts based on failure statistics;
- module to plan the delivery route and schedule of both direct and reverse material flows;
- module to choose a supplier considering the quality of spare parts that they suggest, their location and the proposed terms of delivery;
- module to build supply chains based on decisions made in previous modules; and
- module to analyze the level of risks that can arise in the supply chain suggested by the previous module (Fig. 4).

3.2. Mathematical Background

The constructed problem tree was used to identify critical situations that could cause failures in the logistics system. The reasons are deductively identified and displayed on the tree in the form of intermediate or basic events, depending on the possibility of their further development. In our case, the probabilities of failures of the tree components are connected using the "OR" logical elements; therefore, the probability of the appearance of the upper event G is calculated by formulas (1-4):

$$Q(G) = \sum_{k=1}^{n} q(x_k) \tag{1}$$

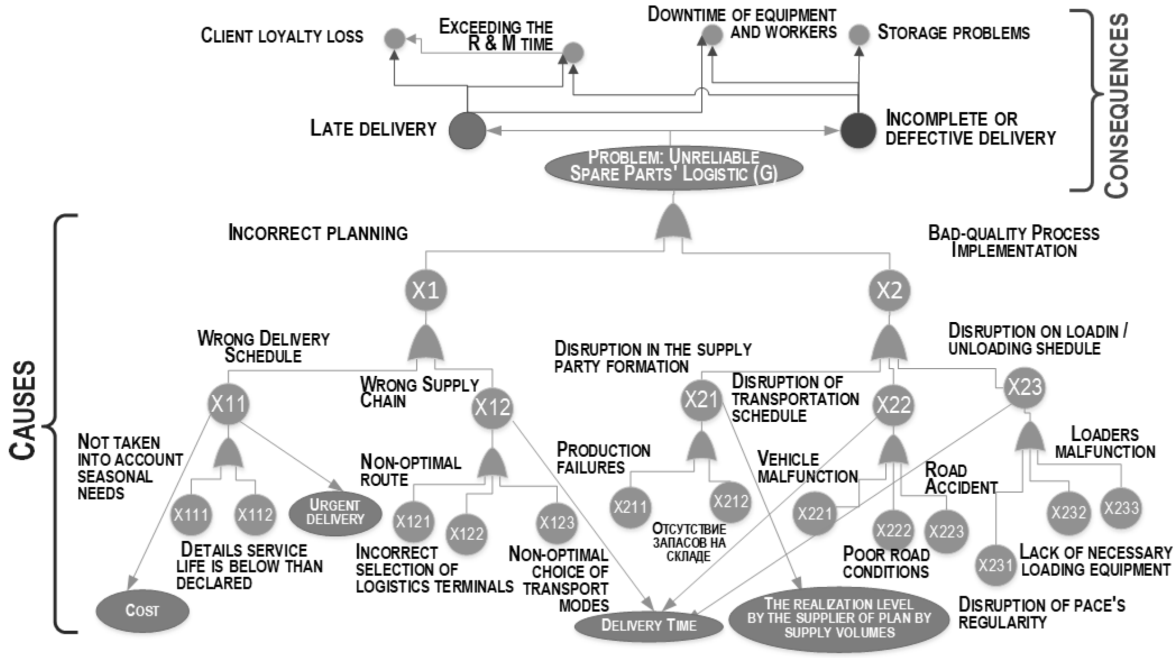


Fig. 3. Problems Tree developed for the spare parts logistics tasks

Fig. 4. Conceptual scheme of the proposed intelligent system

$$q(x_k) = \sum_{j=1}^{m_k} q(x_{kj}) \tag{2}$$

$$q(x_{kj}) = \sum_{p=1}^{r_{kj}} q(x_{kjp}) \tag{3}$$

$$Q(G) = \sum_{k=1}^{n} \sum_{j=1}^{m_k} \sum_{p=1}^{r_{kj}} q(x_{kjp}) \tag{4}$$

where Q is the probability of the upper event (namely, the event G);
n – the number of child events of event G;

m_k, r_{kj} – the number of child events for events x_k, x_{kj}; and

$q(x_k)$, $q(x_{kj})$, $q(x_{kjp})$ – the probabilities of events x_k, x_{kj}, x_{kjp} of the first, second and third levels, respectively.

The probability of the base events $q(x_{kjp})$ was estimated by a statistical analysis of historical data on the operation of the logistics system (Table 1).

Table 1

Probabilities of basic events

Variable	Name	Probability
x_{111}	Not taking into account seasonal requirements	0,26
x_{112}	Details service life is below than declared	0,2
x_{121}	Non-optimal route	0,17
x_{122}	Mistakes when choosing logistic terminals	0,002
x_{123}	Mistakes when choosing modes of transport	0,001
x_{211}	Underproduction	0,02
x_{212}	Lack of inventories in the warehouse	0,25
x_{221}	Vehicle Malfunction	0,05
x_{222}	Poor road conditions	0,03
x_{223}	Road accident	0,01
x_{231}	Disruption of regularity of pace	0,005
x_{232}	Loaders' Malfunction	0,001
x_{233}	Lack of necessary loading mechanisms	0,001

A sensitivity analysis is often performed to determine the "critical" input variables. The critical importance coefficient expresses a numerical relationship between the probability of the main event and the probability of various basic events [26]. The greater the critical importance coefficient for the base event, the more this factor affects the occurrence of the main event. The critical importance coefficient can be calculated using formula (5):

$$I_c(i) = \frac{\Delta Q}{Q} \Big/ \frac{\Delta q_i}{q_i} = \frac{q_i}{Q} I_p(i) \tag{5}$$

where $I_c(i)$ is the critical importance coefficient of the i-th base event, i = 1,2, ... z;

$I_p(i)$ is the probability coefficient of the probability of the i-th main event q_i; it can be calculated using expression (6):

$$I_p(i) = \frac{\partial Q}{\partial q_i} \tag{6}$$

According to expressions (5) and (6), the calculated value of the critical importance coefficient of each base event $I_c(i)$ is determined not only by the value itself but also by the values of other events at this level.

In our case, since the function for calculating the probability of the upper event G is additive, then $I_p(i)$ = 1. Therefore,

$$I_c(i) = \frac{q_i}{Q} \tag{7}$$

The events that make up the problem tree (Fig. 3) lead to various consequences, which vary in degree of significance for the customer. Therefore, the cost of delivery of a spare part depends on the urgency and characteristics of the shipment. Therefore, a violation of the delivery schedule caused by miscalculations of the supplier during planning ultimately affects its cost. The need for urgent deliveries also arises if the quality of spare parts is lower than the level declared by the supplier. In case of repair during the warranty period, the delivery costs are the responsibility of the supplier, but the car manufacturer is responsible for maintaining the operability of the vehicle, according to the warranty, so it should eliminate vehicle's downtime situations because the customer may suffer losses, especially if the vehicle is used in his business.

Most of the events of the problem tree lead to an increase in delivery time, which can lead to an increase in the duration of maintenance and repair, and, consequently, to a loss of customer loyalty and trust in the brand. Therefore, it is necessary to find the best solutions quickly.

Since the tasks of planning routes, scheduling, calculating the size and frequency of deliveries, as well as the probability of failure of spare parts are directly related to the characteristics of the supplier, one of the main tasks is the choice of supplier. For this, it is necessary to take into account the ratio of such characteristics as cost and delivery time, the quality of spare parts, as well as the nomenclature and quantity of supplies.

The decision-making process for choosing a supplier is an important determinant of improving supply chain efficiency. This decision includes the evaluation and selection of the best suppliers, and the subsequent distribution of order volumes between them. This decision leads to a decrease in the cost of procurement and an increase in the competitiveness of the organization. For these reasons, supplier selection is considered a strategic decision in supply chain management.

A significant drawback of the problems tree in solving "choosing a supplier" problem is that it does not consider the interactions and interdependencies between subsystems and system elements, since all the main events are considered independent. However, in comparison with methods for evaluating suppliers based on multi-criteria decisions based on expert evaluations [27], using the problem tree as an information base for developing an evaluation criterion can minimize the "human factor".

Thus, the decision-making process for selecting a new supplier of a specific spare part is a multi-criteria task. This implies the introduction of a super-criterion, i.e. a scalar function of a vector argument, also called a linear convolution:

$$k_0(x) = k_0\big(k_1(x), k_2(x), k_3(x), k_4(x)\big) \tag{8}$$

where $1/k_1(x)$ is the delivery time; $k_2(x)$ is the spare part failure-free operation; $k_3(x)$ is the level of fulfillment of quantitative obligations by this supplier (percentage of delivered spare parts from the total volume of the application); and $1/k_4(x)$ is the price.

By the super-criteria value, one can evaluate alternative solutions and choose the best of them. To do this, we must arrange the alternatives according to the values of the super-criteria. The shape of the function is determined by evaluating the contribution of each criterion to the supercriteria. In our case, according to the obtained expression (4), an additive function is used.

$$k_0(x) = \sum_{i=1}^{4} \frac{\alpha_i \cdot k_i(x)}{S_i} \tag{9}$$

$$\alpha_1(x) = q(x_{121}) + q(x_{122}) + q(x_{123}) + q(x_{221}) + q(x_{222}) + q(x_{223}) + q(x_{231}) + q(x_{232}) + q(x_{233}) \tag{10}$$

$$\alpha_2(x) = q(x_{111}) + q(x_{112}) \tag{11}$$

$$\alpha_3(x) = q(x_{211}) + q(x_{212}) \tag{12}$$

$$\alpha_4(x) = q(x_{111}) + q(x_{112}) \tag{13}$$

First, the coefficients S_i provide the dimensionless of the quantity $k_i(x)/S_i$, since the partial criteria can have different dimensions and then some arithmetic operations, for example, addition, will not make sense. Second, in the necessary cases, with their help, the normalization condition is satisfied. To solve the above problems, we can take S_i as the average value of the corresponding criterion, which was done in this paper. The coefficients α_i reflect the relative contribution of the partial criteria to the super-criterion, i.e. they are weight coefficients. The values of these coefficients for further calculations have been determined in accordance with corporate regulations of the PC "KAMAZ" branded service network and equal to the calculated critical importance coefficients.

The algorithm for selecting a new supplier was presented in our previous work [28]. In the event that several manufacturers supply spare parts of the same nomenclature, and we have statistics on the service life of parts from different manufacturers, we can calculate super-criteria. The obtained values of super-criteria will be the basis for the priority sending of a preliminary application for the supply of spare parts from the supply control center.

3.3. Implementation of software module for multi-criteria suppliers' selection

Information on each spare part, statistics on its failures, information on suppliers, prices for spare parts, statistics of customer calls to service centers and data on urgent deliveries are collected and stored using the first module.

Then, in the second module, the average delivery time of spare parts by suppliers is calculated; in addition, the failure statistics are sent to the STATISTICA package, where the reliability functions are built, and then the evaluation criteria are calculated and a report is generated on the required quantity of each stock item position (Fig. 5).

To minimize logistical risks, the DCN management center should analyze the characteristics of suppliers, and distribute the flows of requests for spare parts taking into account the quality of each supplier, which can be evaluated by formula (13).

Since, according to the calculated critical importance factors for vehicles, the indicator "reliability of spare parts" has the largest weight α_2, a software module was also developed. It can assess the dependence of the reliability index of spare parts on the supplier. To do this, one must first select the name of the spare part and the period during which the supply frequency and failure statistics are estimated. Then, graphs of the quantity of deliveries by suppliers and the specific number of failures for this part are displayed. If in the next period the specific number of breakdowns decreased, then the probable cause is a change in the spare parts supply structure. Therefore, it is necessary to identify which supplier has increased the supply of spare parts. The next strategy will be to further increase the supply from this manufacturer (Fig. 6).

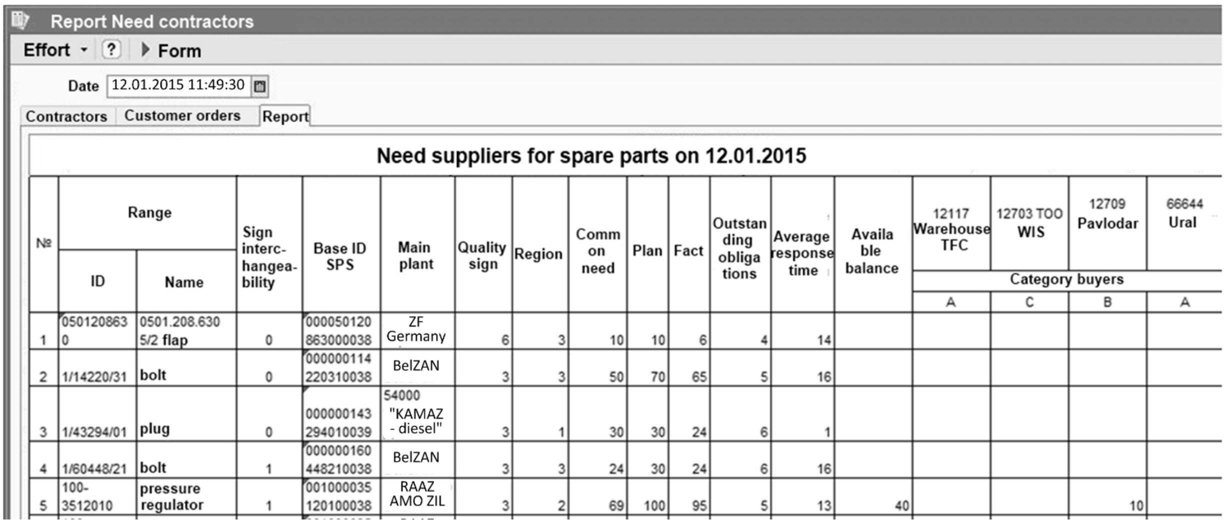
The implementation of the software modules was performed in the RAD Studio environment using the MySQL database.

4. CONCLUSION

In the transition to a circular economy, manufacturers have to examine their supply chains to identify possible risks and to find fundamentally new logistic approaches. We have considered different existing classifications of risks and have suggested our own classification. One of the most important groups of risks is the logistics and transportation risks because they can arise in and influence every stage of the product's lifecycle. To identify the possible problem areas, we have built the Problems Tree, where the unreliability of spare parts logistics is considered the main problem. However, today, it is impossible to consider all possible risks in supply chains and then manage them without the use of modern information technologies. We suggest implementing the multimodule intelligent system performing various functions including delivery routes and schedules planning, supplier selection, spare parts' supply chains building and then identifying and assessing the risks of each managerial decision suggested by the system. All these modules are connected and interact with each other. The module of supplier selection is presented as an example of the system's implementation. In this module, each supplier is evaluated by several parameters including logistics.

References

1. Mo, J.P.T. & Cook, M. Quantitative lifecycle risk analysis of the development of a just-in-time transportation network system. *Advanced Engineering Informatics*. 2018. Vol. 36. P. 76-85.
2. Automotive Parts Remanufacturing Market: Global Industry Analysis and Forecast 2016-2024. Persistence Market Research. 2015. Available at: http://www.persistencemarketresearch.com/market-research/automotive-parts-remanufacturing-market.asp.



Need suppliers for spare parts on 12.01.2015

№	Range ID	Range Name	Sign interc-hangea-bility	Base ID SPS	Main plant	Quality sign	Region	Comm on need	Plan	Fact	Outstan ding obliga tions	Average response time	Availa ble balance	12117 Warehouse TFC	12703 TOO WIS	12709 Pavlodar	66644 Ural
														Category buyers			
														A	C	B	A
1	0501208630	0501.208.630 5/2 flap	0	000050120863000038	ZF Germany	6	3	10	10	6	4	14					
2	1/14220/31	bolt	0	000000114220310038	BelZAN	3	3	50	70	65	5	16					
3	1/43294/01	plug	0	000000143294010039	54000 "KAMAZ - diesel"	3	1	30	30	24	6	1					
4	1/60448/21	bolt	1	000000160448210038	BelZAN	3	3	24	30	24	6	16					
5	100-3512010	pressure regulator	1	001000035120100038	RAAZ AMO ZIL	3	2	69	100	95	5	13	40			10	

Fig. 5. An example of the report on the needs of spare parts

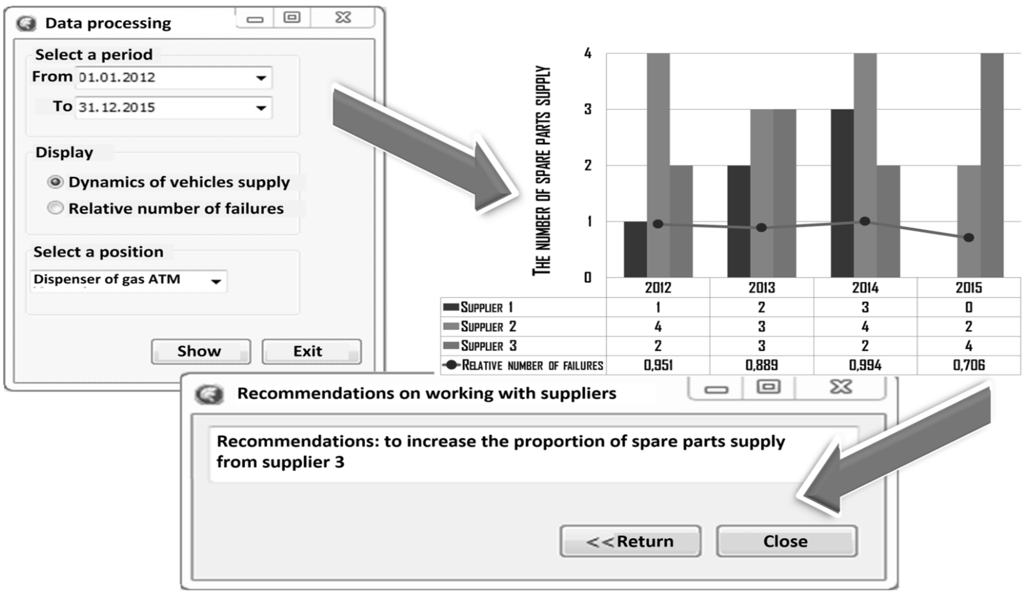


Fig. 6. Module to choose a supplier for improving spare parts logistics

3. Galarza-Urigoitia, N. & Rubio-García, B. & Gascón-Álvarez, J. Predictive maintenance of wind turbine low-speed shafts based on an autonomous ultrasonic system. *Engineering Failure Analysis*. 2019. Vol. 103. P. 481-504.
4. Project Management Institute. A guide to the project management body of knowledge. 1996. PMI Publishing Division. NC, USA.
5. Valitov, S.M. & Sirazetdinova, A.Z. Project risks' management model on an industrial enterprise. *Asian Social Science*. 2014. Vol. 10. No. 21. P. 242-249.
6. Marshall, A. & Ojiako, U. & Wang, V. & et al. Forecasting unknown-unknowns by boosting the risk radar within the risk intelligent organization. *International Journal of Forecasting*. 2019. Vol. 35. No. 2. P. 644-658.
7. Kasprowicz, T. Quantitative assessment of construction risk. *Archives of Civil Engineering*. 2017. Vol. 63. No. 2. P. 55-66.
8. Makarova, I. & et al. Problems, risks and prospects of ecological safety's increase while transition to green transport. In: Nathanail, E. & Karakikes, I. (eds). Data Analytics: Paving the Way to

Sustainable Urban Mobility. CSUM 2018. *Advances in Intelligent Systems and Computing.* 2018. Vol. 879. P. 172-180. Springer, Cham.
9. Jaber, J.O. & Elkarmi, F. & Kostas, A. Employment of renewable energy in Jordan: Current status, SWOT and problem analysis. *Renewable and Sustainable Energy Reviews*. 2015. Vol. 49. P. 490-499.
10. Wang, F. & et al. Fault tree analysis of the causes of urban smog events associated with vehicle exhaust emissions: A case study in Jinan, China. *Science of the Total Environment.* 2019. Vol. 668. P. 245-253.
11. Lokuge, W. & et al. Predicting the probability of failure of timber bridges using fault tree analysis. *Structure and Infrastructure Engineering.* 2019. Vol. 15. No. 6. P. 783-797.
12. Sun, Y. & Deng, D. Research on the defects and improvement of internal control of scientific research funds in colleges and universities based on FMEA model. *Proceedings of the 2017 International Conference on Service Systems and Service Management*. Dalian. 2017. P. 1-4.
13. Lombardi, M.E. FMEA for Lean Manufacturing. *Proceedings of the 2011 IEEE/SEMI Advanced Semiconductor Manufacturing Conference*. Saratoga Springs, NY. 2011. P. 1-2.
14. Kowsari, M. & et al. Calibration of ground motion models to Icelandic peak ground acceleration data using Bayesian Markov Chain Monte Carlo simulation. *Bulletin of Earthquake Engineering.* 2019. Vol. 17. No. 6. P. 2841-2870.
15. Li, W. & He, M. & Sun, Y. & Cao, Q. A proactive operational risk identification and analysis framework based on the integration of ACAT and FRAM. *Reliability Engineering and System Safety.* 2019. Vol. 186. P. 101-109.
16. Ma, D. & et al. Constructing Bayesian network by integrating FMEA with FTA. *Proceedings of the Fourth International Conference on Instrumentation and Measurement. Computer, Communication and Control*. Harbin. 2014. P. 696-700.
17. Guo, J. & et al. Hydro-pneumatic suspension gasbag reliability improvement based on FMEA and FTA. *Proceedings of the 10th International Conference on Reliability, Maintainability and Safety (ICRMS).* Guangzhou. 2014. P. 592-594.
18. Sarbayev, M. & Yang, M. & Wang, H. Risk assessment of process systems by mapping fault tree into artificial neural network. *Journal of Loss Prevention in the Process Industries.* 2019. Vol. 60. P. 203-212.
19. Zarbakhshnia, N. & Soleimani, H. & Ghaderi, H. Sustainable third-party reverse logistics provider evaluation and selection using fuzzy SWARA and developed fuzzy COPRAS in the presence of risk criteria. *Applied Soft Computing.* 2018. Vol. 65. P. 307-319.
20. Prakasha, A. & Agarwala, A. & Kumar, A. Risk assessment in automobile supply chain. *Materials Today: Proceedings.* 2018. Vol. 5. P. 3571-3580.
21. Wang, L. & Foerst, K. & Zimmermann, F. Supply chain risk management in the automotive industry: cross-functional and multi-tier perspectives. *Dynamic and Seamless Integration of Production, Logistics and Traffic*. Abele, E. & et al. (eds.). Switzerland: Springer International Publishing. 2017. P. 119-144.
22. Galkin, A. & Dolia, C. & Davidich, N. The role of consumers in logistics systems transp. *Research Procedia.* 2017. Vol. 27. P. 1187-1194.
23. Zimmer, K. & Fröhling, M. & Breun, P. & Schultmann, F. Assessing social risks of global supply chains: A quantitative analytical approach and its application to supplier selection in the German automotive industry. *Journal of Cleaner Production.* 2017. Vol. 149. P. 96-109.
24. Yi, X.J. & Shi, J. & Dhillon, B.S. & et al. A new reliability analysis method for repairable systems with closed-loop feedback links. *Qual Reliab Engng Int.* 2018. Vol. 34. P. 298-332.
25. Rezapour, S. & Farahani, R.Z. & Pourakbar, M. Resilient supply chain network design under competition: A case study. *European Journal of Operational Research.* 2017. Vol. 259. P. 1017-1035.
26. Sarbayev, M. & Yang, M. & Wang, H. Risk assessment of process systems by mapping fault tree into artificial neural network. *Journal of Loss Prevention in the Process Industries*. 2019. Vol. 60. P. 203-212.

27. Rashidi, K. & Cullinane, K. A comparison of fuzzy DEA and fuzzy TOPSIS in sustainable supplier selection: Implications for sourcing strategy. *Expert Systems with Applications*. 2019. Vol. 121. P. 266-281.
28. Makarova, I. & Shubenkova, K. & Buyvol, P. & Mukhametdinov, E. Intellectualization of the spare parts supplier selection by the analysis of multi-criterial solutions. *Lecture Notes in Networks and Systems.* 2018. Vol. 36. P. 300-310.

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