SUPPLY CHAIN RISK MANAGEMENT BY MONTE CARLO METHOD

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Abstract. In this paper, the conceptual model of risk-based cost estimation for completing tasks within supply chain is presented. This model is a hybrid. Its main unit is based on Monte Carlo Simulation (MCS). Due to the fact that the important and difficult to evaluate input information is vector of risk-occur probabilities the use of artificial intelligence method was proposed. The model assumes the use of fuzzy logic or artificial neural networks – depending on the availability of historical data. The presented model could provide support to managers in making valuation decisions regarding various tasks in supply chain management.

Keywords: project management, decision support systems, neural networks, fuzzy logic

ZARZĄDZANIE RYZYKIEM ŁAŃCUCHA DOSTAW ZA POMOCĄ METODY MONTE CARLO

Streszczenie. W artykule zaprezentowano przykład zastosowania hybrydowego systemu wspomagania decyzji w kontekście zarządzania ryzykiem w łańcuchu dostaw. Główny moduł sterownika bazuje na koncepcji symulacji Monte Carlo. Wektor danych wejściowych zawiera istotne informacje, których wyrażenie w postaci zmiennych ilościowych stanowi wyzwanie, w związku z czym zaproponowano użycie sztucznej inteligencji. W zależności od dostępności do danych historycznych, sterownik decyzyjny zastosuje sieci neuronowe lub logikę rozmytą. Zaprezentowane rozwiązanie może stanowić wsparcie dla menedżerów podczas podejmowania decyzji będących odpowiedzią na różnorodne ryzyka w obszarze zarządzania łańcuchem dostaw.

Słowa kluczowe: zarządzanie projektami, systemy wspomagania decyzji, sieci neuronowe, logika rozmyta

1. Introduction to risk management concept

Observation of current megatrends and the way companies run their business today shows that the key factors for enhancing competitiveness are innovation in the area of product, technology, organization and marketing. Introducing new products and services [8] and increasing the level of business processes is becoming increasingly difficult. The reason of this fact is high cost of improvements and strong competition – especially from large companies. In order to increase efficiency, companies try to optimize processes, which often involves cooperation in many areas of business. Cooperation involves the exchange of information and goods (parts, products) between economic operators. The aim of the co-operation is to minimize costs and increase the flexibility of the company, for example, the readiness to complete complex orders. Cooperation necessitates delegating some tasks outside of one's own organization, which in turn increases the risk of various types of disruptions. These disruptions can affect the supply chain, supply, transportation, production and demand fluctuation (figure 1).
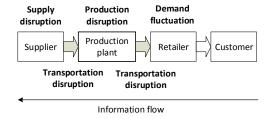

Fig. 1. Different disruptions in a manufacturing supply chain system [7]

Handling of orders where there is a high risk of supply chain disruptions is most often associated with the need for a design approach, which in turn requires time scheduling, resources and costs management. Precise cost calculation and evaluation of time execution for these types of orders is a must, as the customer agreement requires, among other things, a delivery deadline and price.

Examples of challenges that require specific supply chain risk management are:

- complex construction and infrastructure projects,
- managing of transport of large objects,
- organization of transport of elements requiring multimodal transport (over long distances, eg transcontinental transport),
- production organization in the automotive industry.

In literature, there are various attempts of risk classification which prove that risk is a multidimensional and complex phenomenon [9]. Risk modelling is a developing and ongoing process [13] what makes the risk one of the main reasons for the erroneous cost calculations of projects [10]. There is a crucial necessity for a cost estimation method that covers all estimation factors. There are many proposals that suffer from a lack of scientific justification for the results, that is, lack of describing how technically the results have been achieved [2].

For projects requiring supply chain management, there is a significant increase in the risk of failure to meet deadlines and over budget. Successful estimation of prices for differentiated orders requiring complex logistical support is more difficult, the more the factors that the contractor has limited influence or that are completely independent of him. Such factors include: cooperation, currency fluctuations, severe construction and material requirements, or accidents at work [3]. In the case of exceeding the deadline, contractors are subject to contractual penalties, customer loss, and worse, the depreciation of reputation, which is a crucial value and is a strategic success factor.

Under these circumstances, it is an important challenge to develop an effective risk minimization approach for time-cost valuation of atypical supply chain management tasks [14].

There are three criteria for measure the effectiveness of the cost estimation method for project tasks requiring supply chain management due to the risk associated with their implementation. These are: predictability, speed and ease of use. There is no doubt that to meet these criteria IT-based techniques should be used. In this paper an expert system for decision support in the valuation process was described. There are many types of software that integrate business processes and logistics, but in this case the problem is more sophisticated. The problem is the connection of the kinds of disruptions with quantitative results – such as costs and time.

Literature analysis allows us to identify some of the most commonly used methods of estimating project risk. These include the following methods: Fuzzy Logic (FL), Artificial Neural Networks (ANN), Monte Carlo Simulation (MCS), Support Vector Machines (SVM) [11].

Fuzzy logic (FL) can be used in the estimation of time-cost risk especially when historical data are not accessible [1, 4, 5, 12]. In such a case the good idea is to use heuristics. For example the known methods are the Delphi method [6] or the Brainstorming method. Heuristics are recorded in linguistic form as so called reasoning rules, which in the next stage constitute the core of the fuzzy inference system. In this method, in addition to the rules of

inference, it is necessary to select the appropriate inputs, membership functions and defuzzification method.

The most commonly used ANN variant is multilayer perceptron (MLP). In this shape the ANN method can be effective only if we have a sufficiently large number of relevant historical data from which to create a training, test, and validation sets. It is also difficult to find cause-and-effect relationships between properly chosen input variables and the cost or the completion date of the order.

The popularity of Monte Carlo Simulation is due to its versatility and ease of use. The MCS method is a quantitative method that involves assigning individual types of risk to probability of its occurrence. The consequence of an unexpected occurrence may be an unplanned change in the cost and completion date of the order or contract which can be treated as a project.

The weak point of this method is the need for deterministic determining probabilities of the various types of project risks. Typically, this is done by one expert or group of experts with experience in the field. Still, the decision on the appointment of the assessed level of risk events is a decision laden with a high degree of subjectivity. This is a major drawback of the MCS method.

The SVM method is somewhat similar to the ANN/MLP method because of the need to have a historical set of data for the training process. Compared to ANN, the strength of the SVM method is to find a global minimum and resistance to overtraining. The disadvantage is the slow training by which calculations take a long time.

As can be seen from the above description, each of these methods has significant constraints that hinder its application in relation to cost estimation and likewise the duration of individual contracts that may be considered as separate design tasks.

In order to eliminate the disadvantage of subjectivity, present in the classical version of the MCS method, artificial intelligence can be applied in the process of estimating the probability of occurrence of individual project risks.

For companies that do not have historical data in shape that would be ready to be used to train the neural network or the SVM driver, the method based on heuristics can be implemented. One such method is Fuzzy Logic.

It can be argued that the use of hybrid system using the artificial intelligence method to determine the probability of project risks in Monte Carlo Simulation will improve the efficiency of this method. The improvement is achieved by minimizing the subjectivity of the decisions being made.

The second thesis states that determining the probability of design risks by artificial intelligence methods is more reliable than the deterministic method – based on subjective expert judgment.

2. Concept of risk management system

Table 1 shows an example of how to calculate project risks related to supply chain disruptions using Monte Carlo simulations. Column 1 contains the Risk Breakdown Structure. Column 2 lists the identified disruptions. Column 3 contains the subjective probability of occurrence of a given type of risk.

Column 4 contains the cost of risk to be incurred if it occurs. By analogy, the risk of exceeding the project completion deadline can be set, replacing the cost with time. In that case the set of risks in column 2 should also be changed.

Column 5 contains the expected value of the risk that is the product of the columns 3 and 4. The sum of the column 5 is 621.40 EUR. This is a weak spot because it is not enough to cover the cost of a single R-2 risk (900.00 PLN). Columns 6 and 7 allow running simulations of many risk variants. Column 6 uses function generating the random real numbers in the interval ⟨0,1⟩. Column 7 contains the following logical conditional formula: if column 3 is bigger or equal column 6 then column 7 is equal column 4.

Table 1. Risks of disruptions in supply chain

Risk Breakdown Structure (DBS)	Identified disruptions	Probability	Cost [PLN]	Calculated cost [PLN]	Random risk	Simulation results [PLN]
1	2	3	4	5	6	7
R-1	Cooperation disruptions	0.23	600.00	138.00	0,05	**600.00**
R-2	Damage to shipments in transit	0.09	900.00	81.00	0,64	
R-3	Dealy in transport	0.12	500.00	60.00	0,01	
R-4	Production disruptions	0.45	300.00	135.00	0,99	
R-5	Suppliers delays	0.22	160.00	35,20	0,75	
R-6	Demand fluctuations	0.36	490.00	176,40	0,27	**490.00**
O-1	Exchange rate differences in currency settlements	0.07	-60.00	-4,20	0,20	
Sum:				**621.40**		**1090.00**

The sum of column 7 contains the cost of risk in a simulated single case. After making 2000 simulations using the random number generator we obtain a cumulative probability graph (cumulative distribution), which is shown in Figure 2.

The horizontal axis contains risk costs for each scenario. On the vertical axis, the population of scenarios, calculated as a percentage of all possible situations. The most favorable scenario assumes that the project risk will result in additional revenue (negative cost), but the probability of such a scenario is close to zero.

When planning the cost of ordering a supply chain, two opposing goals should be considered: minimizing costs and minimizing the effects of disruptions. As shown in Figure 2, if we increase the budget by an additional PLN 2500, which we will spend on minimizing project risk, we will almost certainly be 100% sure that the project will fit in the budget. The disadvantage of such a solution is that it costs too much to make the customer to pay for them. That is why there is a need to look for compromise solutions. It can be assumed that the appropriate compromise is the risk cost probability oscillating around 80%, which corresponds to 1000 PLN additional cost associated with project risks. It can be noticed that 80% of the population of all scenarios is to the left of this amount.
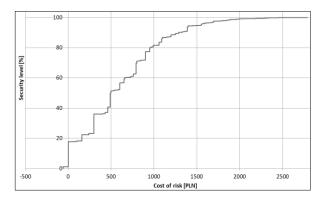

Fig. 2. Security level vs. Cost of risk

Artificial Intelligence can be used to remove the element of subjectivity in the probability selection of individual risks (tab. 1, column 3). The algorithm for designing a hybrid design risk assessment system is shown in Figure 3.

The first step in the design process is to identify all potential risks that may affect the cost and timing of business contracts. The next step is to assign the identified quantitative risk measures. They provide input for individual decision modules that determine the probability of occurrence of particular risks.
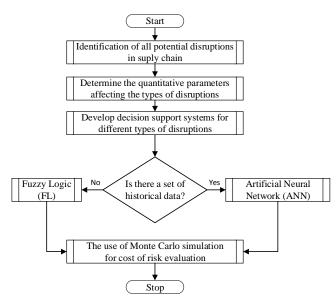
Fig. 3. Algorithm for designing an evaluation system for project risk costs calculation in supply chain management

If the system can be powered by properly prepared (tabulated) historical data, you can create an ANN based decision subsystem. Otherwise FL can be used.

The SVM method has been omitted in the present considerations because of too much computing slowness, thus failing to meet the previously defined criteria for an appropriate speed of operation and, consequently, also the ease of use criterion.

It is important to note that when determining the input vectors for each module that determines the probability of risk the availability of data should be taken into account.

For example, it can be assumed that the risk R-1 (subcontractor errors) depends on the criteria presented in Table 2 corresponding to the intelligent project risk estimation subsystem presented in Fig.4.

Table 2. Inputs features for evaluation risk of disruption R-1 "Cooperation disruptions"

IBS	Input feature name	Measure
1	*2*	*3*
Input-1	Number of tasks in the supply chain requiring external cooperation services	[pcs]
Input-2	The lowest rating of the co-operative's history among the external service providers involved in the completing of the order	[%]
Input-3	The lowest result from external audits carried out at the contractors participating in the completing of the order	[1,2,..,10]

Column 3 in Table 2 contains methods for measuring the input characteristics of the R-1 module. While the measurement of the Input-1 feature is quite obvious, the situation is getting complicated by Input-2 and Input-3.

For example, to determine the percentage value of the Input-2 it is necessary to evaluate the timeliness of all subcontractors. It is possible to set the number of all orders in the past from given subcontractor (c) and the total number of claims from given subcontractor (S_o). By setting the ratio c to S_o we can get an Input-2 percentage.

Input-3 may take values from 1 to 10, where 1 denotes a low quality rating. Input-3 needs to have the results of audits, taking into account the quality assurance systems of each of the partners. It should be noticed that, despite the fact that the values of the Input-3 characteristics are determined by experts, they are still reliable. They are the result of the analysis of appropriate measures defined within the internal quality systems of subcontractors. If the system is certified (eg ISO 9001), evaluation of the quality system based on the indicators is much easier. Otherwise, the evaluation requires dedicated methods of Input-3 reliable measurement.
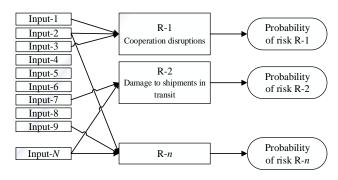

Fig. 4. Intelligent project risk estimation subsystem

Generated at the outputs of intelligent subsystems the probability values of the individual project risks are inputs to the Monte Carlo Simulation risk calculation system.

Figure 4 presents an intelligent subsystem for project risk estimation. On the left is an *N*-element vector of identified inputs. These are features that may affect the *n*-elemental set of risks. As a rule, always $N \geq n$.

As can be seen from Fig. 4, one input (e.g. Input-2) can supply two or more units for estimating probabilities of R-*i* risk.

Figure 5 shows a complete hybrid scheme for project risk calculations within the supply chain. It can be seen that the system consists of three main subsystems – Fuzzy Logic, Artificial Neural Networks and Monte Carlo Simulation (MCS).
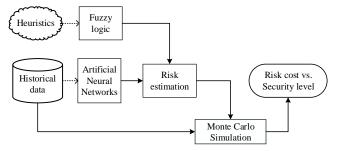

Fig. 5. Hybrid system for project risk costs calculation in supply chain management

Fig. 6 presents a model of fuzzy controller operation which objective is R-1 risk value estimation. Each of the three rows of membership functions corresponds to one fuzzification rule. The first three columns of the membership function correspond to the three input variables of the R-1 controller (see Fig. 4). The last, fourth column, reflects the output parameter which is computed through the determination of the centroid of a plane figure. It is the result of the compilation of several inference rule graphs (right bottom corner of Fig. 6). In the present example, the R-1 output variable is 0.402.

Figure 7 shows the spatial diagrams illustrating relationships between two selected input variables: Input-1 (number of tasks in the supply chain requiring external cooperation services) and Input-2 (the lowest rating of the co-operative's history among the external service providers involved in the completing of the order). The irregular shape of the surface indicates a complex function which transfer inputs into outputs. Therefore, it can be obvious that the try of describing these relationships with a mathematical formula would be very difficult. This fact explains to a high extent the sense and benefits of using fuzzy logic to solve problems connected with decision support systems and processes.
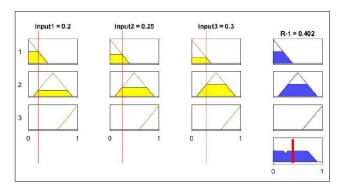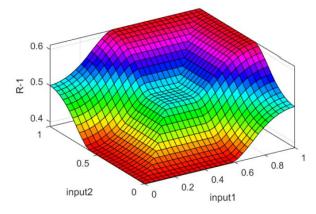
Fig. 6. Inference rules in fuzzy logic unit

Fig. 7. Response surface of the fuzzy controller

3. Remarks and conclusion

This paper presents the way of implementation of Monte Carlo Simulation and artificial intelligence for the problem of risk calculation in supply chain management. Individual character of particular supply chain tasks allows to treat them as separated projects. A model of the hybrid decision support system, consisting of historical data, heuristics, fuzzy logic, artificial neural networks, risk assessment module and MCS cost estimation module, was proposed. An appropriate algorithm for designing an evaluation system for project risk costs calculation in supply chain management was developed.

The decision support system has a multistage structure. It means that the output of the previous module is the input of the next module. For example, the results of the fuzzy controller are input data for the subsystem for risk cost estimation with the use of Monte Carlo Simulation.

For a method to be effective and effective, it must be easy to apply and deliver results in no time. The MCS method is based on an iterative algorithm. This is the more accurate the more iteration is done by it, but subsequent iterations lengthen the calculation time. It is therefore necessary to establish a compromise between the desired accuracy of risk cost estimation and the number of computed iterations.

For ANN that require historical data, an automatic training mechanism should be included. Over time, the number of training cases increases. These data should be successively attached to the training set and participate in the network training process.

In this paper the two initially formulated, mutually complementing hypotheses stated that the use of hybrid systems based on MCS and artificial intelligence allow to get accurate results of project risk calculations. The truthfulness of the hypotheses was confirmed. It was possible by introduction of logical and coherent vision of reasoning rules, which could replace the subjective hence imperfect decisions taken by human.

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