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An Intelligent System to Predict Risk and Costs of Cargo Thefts in Road Transport

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Abstract

The article looks at the simulations of the possibility of theft risk occurrences with taking into account different types of cargo, its price and a carriage phase. The risk analysis was conducted by using original algorithms developed on the basis of artificial neural networks that take into account, among others, the probability of the cargo theft risk in a particular stage of the order for different types of cargo. The authors specify the forecasted loss values that refer to the type of stolen cargo, including penalties depending on the stage of the carriage. The research and the method described in this article enable the engineers to create a tool/program that facilitates the process of making decisions about additional cargo insurance or the use of monitoring systems for the location and parameters of the cargo. The method can also be used by the insurance companies to determine rates for cargo insurance.

Keywords: road transport, cargo parameters monitoring, risk identification, simulation of theft risk, transport risk and costs

1. Introduction

The implementation of effective risk management in related chain links has a significant impact on the security of the entire flow process. It means that from the supply chain point of view, the risk analysis for each element of the supply chain, including the identification of occurring risks, is extremely important. In the transport process and in other links of the chain, the identification of places susceptible to fault and the recognition of current and potential risks are needed. The Transported Asset Protection Association's (TAPA) reported a five-year growth of cargo crimes in 2015 with 1,515 recorded freight thefts representing a 37.4 % increase year-on-year. In the United States in 2015, the average cargo theft loss value per incident was $187,490, but 10 cargo thefts worth more than $1 million were also recorded.

Numerous articles deal with issues related to risk management in a supply chain. Risk assessment in maritime transport is a frequently discussed problem. Bichou [1] focuses on maritime security assessment models, Celik et al. offer an analytical foundation for the shipping accident investigation process [2], while [3] explore and analyse risks in container shipping operations from a logistics perspective. The multimodal maritime supply chain risk assessment presented in [4] incorporates perspectives from different parts of the chain and presents a new framework for categorizing the risks in terms of their driver factors in order to assess the overall impact on the performance of the supply chain. Despite such great interest in this field, the concept of supply chain risk management has still to be developed. The analysis of this problem in terms of understanding business requirements is presented in [5].

Mean-variance (MV) theory is included in many papers, and it is considered as a well-proven approach for conducting risk analysis in stochastic supply chain operational models. In [6] is presented a technical review of a supply chain risk

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analysis with mean-variance (MV) models. They classify the literature into three major areas: single-echelon problems, multi-echelon supply chain problems, and supply chain problems with information updating.

In terms of cargo theft in a supply chain many analysis was also conducted. Risk analysis and assessment of a cargo theft are presented for example by [7]. Conducted analysis is based on the data in the Transported Asset Protection Association's [8] transport-related crime database. The results of this analysis showed that practitioners could understand and address cargo theft risks more effectively when they examine the frequency and impact of such theft separately. [9] In their work identify and describes the scale of cargo theft in the European pharmaceutical supply chain. It turns out that there are relatively few attacks by year, but taking into account the value of pharmaceuticals, this group of product is placed as one of the top targets for criminals. [10] Examine the patterns of reported cargo thefts at non-secure parking facilities in Europe, with respect to stolen value, frequency and incident category. It found outs that cargo thefts are more of a volume crime than high-value thefts. In addition, seasonal variations were seen in these thefts, and the most common type was an intrusion on weekdays during winter.

Descriptions of the methods and models that are proposed to estimate the probability of risk occurring in a transport chain can be found in many works. The risk assessment and the methods and applications are presented in, e.g. [11-14]. Rausand described, inter alia, accident models, risk assessment process, hazard identification or uncertainty and sensitivity analysis. De Jong et al. presented a micro-simulation model which simulates the choice of shipment size and transport chain while Zio used the Monte Carlo simulation method for system reliability and risk analysis. Urciuoli [16] in his work presented a methodology that uses the quantitative risk assessment approach (QRA) to compare costs and benefits (in a form of risk reductions) of security solutions for road transport operations against theft. He generated random data from triangular distributions on the basis of experts' answers, and simulated their impact with the use of the Monte Carlo techniques. In professional literature, numerous articles refer to maritime transport [1]. Analyses of maritime piracy and robbery related incidents in terms of the major influencing factors such as ship characteristics are presented in [15]. Authors developed an analytical model for maritime piracy and robbery assessment taking into account the characteristics of a ship, environment conditions and the maritime security in an integrated manner. Such a model can be used by maritime stakeholders to make cost-effective anti-piracy decisions in their operations under uncertainties. Theft in a transport supply chain is still a big problem for transport companies and there is still need to create an intelligent system to predict risky situations.

In order to determine the probability of risk and cost caused by cargo theft in a transport chain, the authors propose an original method of risk and cost prediction. The method can be used to support decisions about additional cargo insurance for high risk of theft transport cases or to implement monitoring systems for the location or parameters of the cargo.

2. Overview of Parameters Monitoring Systems

Intermodal shipments are often characterized by a high value of transported goods, mass character and large transport distances. Moreover, they often require a change in the carrier and even the mode of transportation. Therefore, the owners of intermodal freight and rail operators demand information not only about the exact location of the cargo, but also the conditions of transport [17]. Most of the technological solutions such as GPS modules are universal and adapted to the requirements of the customer, regardless whether it comes to industrial tools, dangerous chemicals, expensive drugs, exotic or high-quality food products. Most units commercially available can monitor if the specified temperature range is respected, they can measure shock resistance or register moisture inside the load unit, and record the exposure to solar and electromagnetic radiation. The units used in intermodal transport are designed specifically for monitoring containers. They are usually mounted on the outer wall of the container. They have sensors on the door or in the inside of the container and they are sensitive to atmospheric conditions. An installed device receives the location data from GPS satellites. The information is then sent via data transmission by mobile network to the server, and it is processed. When a vehicle is located out of the range of the mobile network, e.g. in the middle of the ocean during a storm, the history of the position is not lost. If the GPS module cannot send the position data, it saves it in its internal position and sends it when possible. The modules used in the monitoring of cargo transportation are highly prevalent on the market and are usually in the form of independent modules.

According to destination and monitoring capabilities, the following systems can be distinguished:

(1) Systems to monitor cargo location: The location device with a GPS receiver installed in the vehicle collects the data on its current position. Then, using GSM/GPRS network, the data are sent to the monitoring server to which the user receives access. The application allows an electronic tracking of cargo by monitoring its location and safety. By using SaaS solution (Software as a Service) and a capability to support almost every tagging technology (GPS, GPRS, RFID and others), it is possible to track and monitor cargo units almost all over the world.

It is also possible to track cargo in an indirect way thanks to the information exchange between operators, intermodal carriers and customers. Such systems do not use GPS modules or GPRS data transmission. An approximate location of cargo can be checked at each stage of the transport chain following the number of the container. Such systems do not allow the precise position of the load to be identified, but neither do they require the installation of additional equipment for intermodal units.

(2) Systems to monitor cargo specific parameters: Such a system makes it possible not only to identify the exact location of the cargo unit, but also allows one to specify the actual parameters of the load. With the ability to define custom POIs (Points of Interests) and assign to them the maximum time within which the cargo should leave the defined area, it is possible to automatically generate notifications. This solution makes it possible to supervise costs resulting from the long waiting time for transshipment in a terminal or warehouse. The system offers automatic notification of temperature changes in relation to the established range. The system also includes the measurement of various parameters of the load, for example, temperature, pressure, leaks and other safety-related parameters.

Dedicated systems should also be mentioned, for example, systems for ports and container terminals. These are usually online applications dedicated to seaports and their clients, offering a wide range of functionality (TOS type systems - Terminal Operating System). The position location of containers in the harbour is one of the basic system options. Usually it is not required to mount a GPS module to container because such an application is based on a virtual model, i.e. every container, which is inserted on storage square, has an assigned specific location. Linking the container number to a specific place of storage allows the system to visualize the stored units in the terminal. This solution provides high accuracy, but in the case of rare errors makes it difficult to locate the container. Apart from indicating the location on the square storage, this system allows showing the status of the container, for example, its placing on the ship, unloading, storage, loading wagon/trailer, etc.

Another group of systems worth mentioning includes systems to monitor the location and parameters of the mode of transportation. Such systems help supervise individual units by using GPS locators. It is also possible to apply additional sensors that increase the number of monitored parameters. Data handling from the locators and using a special set of statistical tools may be obtained from a web browser. Sometimes, such a system does not provide direct possibilities for monitoring the position of an intermodal unit. Thanks to the information concerning the means of transportation and cargoes on it, it is possible to link the means of transportation location to the location of the container. Additional services and functionality of the system may permit, inter alia, the registration of constant parameters (registration number of the vehicle, driver and vehicle data), the registration of exploitation parameters (vehicle mileage, pressure, and digital signals), information about the faults, device status information, and recording service information for diagnosis.

The discussed modules used for monitoring the parameters of containers can also be more advanced allowing cargo protection, for example, checking if the container doors are open, checking if there was any movement, controlling lights or other events deviating from standard inside the container. In short, they can monitor everything that can have an impact on the transported cargo. The available modules allow the following: monitoring the cargo location, recording transport conditions, guarding the permitted range of conditions, temperature, humidity and shock measurement, reporting container movement, protecting cargo by detecting unwanted actions of third parties, and the history of the cargo movement.

3. Methodology

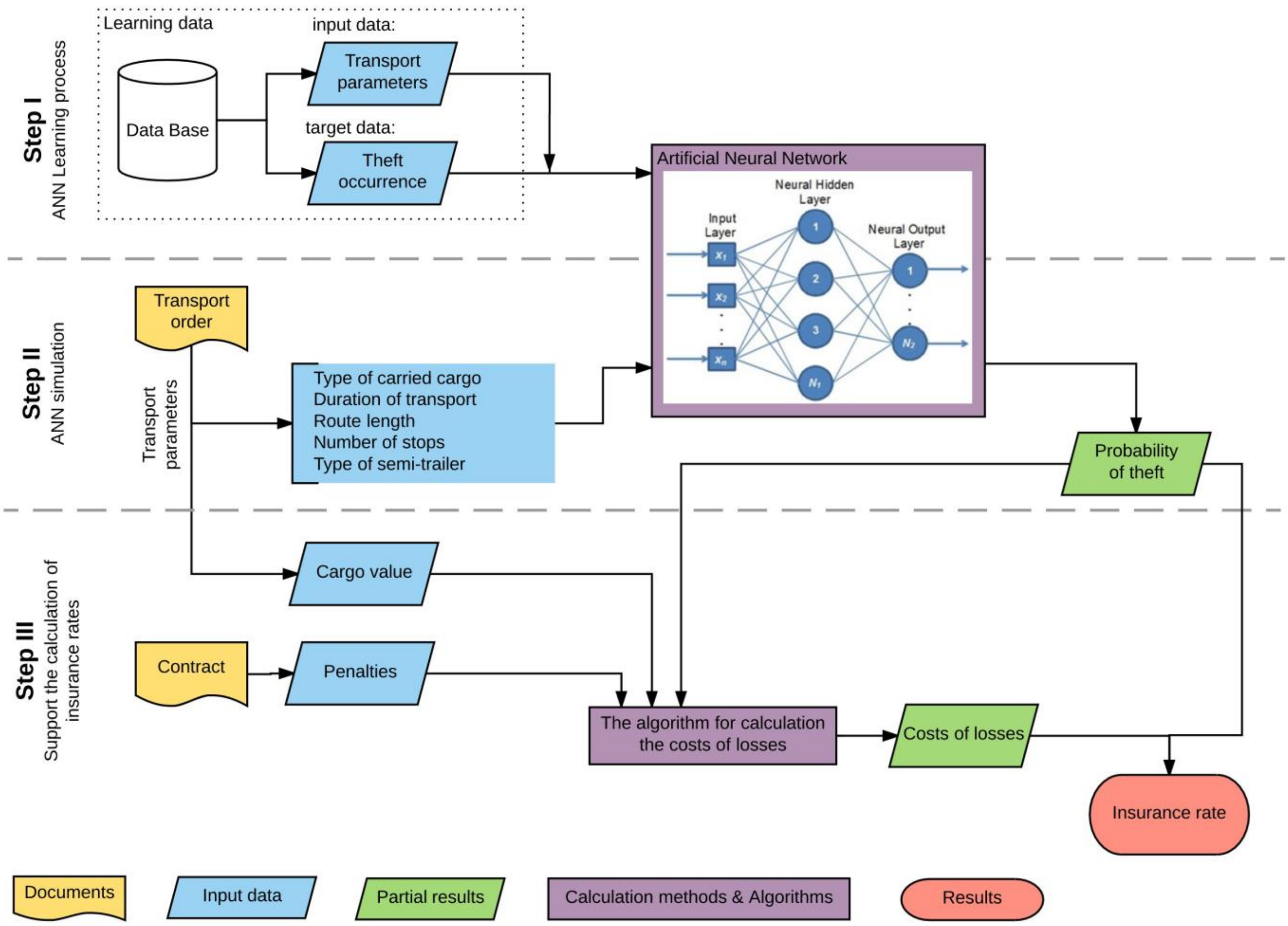


Fig. 1 The method of theft probability and cost prediction

The method shown in Fig. 1 consists of three steps: ANN learning, probability simulation and cost of risk calculation. The obtained results are helpful in determining cargo insurance rates. The Matlab R2015a software was used for modelling artificial neural networks. The results were analyzed using the Minitab 17 and Statgraphics Centurion XVII. The description of each step is shown below.

(1) Step I

The first step in the proposed method is to determine, on the basis of artificial neural networks, the probability of theft of the transported cargo. For this purpose, it was necessary to create a database containing such data as transport parameters and cases of theft occurrence. Transport parameters may include, inter alia, the type of carried cargo, country/region of transport, duration of transport, distance, number of stops and the type of semi-trailer.

A feed forward network was used for the simulation. The created artificial neural network (ANN) consists of three hidden layers (containing respectively 4, 10 and 6 neurons) and one output layer. As an activation, the tangensoidal function was used. The Levenberg-Marquardt backpropagation method was used as the learning algorithm. The selection of an artificial neural network structure was based on the method of subsequent approximations. The network structure selection was made on the basis of the mean square error (mse).

Fig. 2 shows the structure of the network. Fig. 3 shows the best validation performance. Transport parameters (type of carried cargo, duration of transport, distance, number of stops and type of semi-trailer) were used as a learning input data. The cases of the theft were implemented as a learning target.

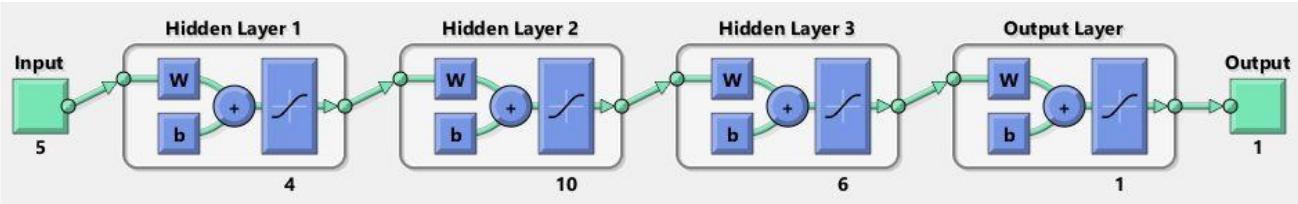


Fig. 2 Structure of artificial neural network

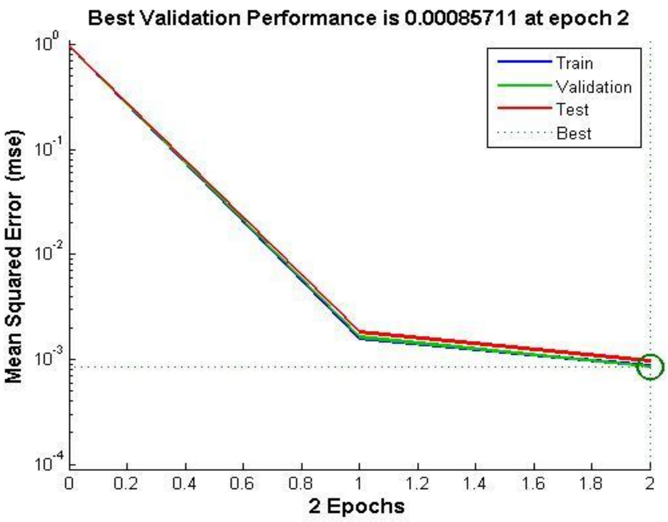


Fig. 3 Best validation performance

(2) Step II

The purpose of the next step in the presented method is to perform, on the basis of the transport order and the type of carried cargo, 120,000 simulations (10,000 simulations for each type of cargo) to determine the probability of theft. As a result, it is possible to determine the probability of theft for each transport order.

(3) Step III

The aim of the third step is to determine the amount of insurance for the transport in which the increased risk of theft is identified. Therefore, one can check the cost of loss that would occur for such a case. This is possible to be calculated on the basis of the value of the cargo contained in the transport order, the value of the contractual penalties and the probability of theft for a particular case. The algorithm for calculating the costs of loss is presented below.

$$K = \sum_{i=1}^{n} w_i + \sum_{j=1}^{dy} p_j + \sum_{k=1}^{da} p_k \tag{1}$$

where w_i is value of order; n is number of orders in transport; p_j is penalty for each day of delivery delay; dy is number of days of delivery delay; p_k is penalty for lack of goods; da- number of orders with lack.

The authors also distinguished the situations where the carrier was equipped with a system for monitoring parameters of the transportation and the carried cargo. Thanks to that the costs of undesirable incidents, like theft or container loss, could be reduced. Moreover, it is possible to synchronize transshipment process, reduce time of storage in the terminal – in case a vessel arrives faster than it is expected, and reduce problems with the determination of loading and unloading terms.

The above-presented method can be helpful in setting insurance rates for transport cases with higher risk of theft.

4. Example

Based on the proposed method, it was checked whether the type of carried cargo had an outflow on the probability of theft. In the first step, the data generated from statistical data was used to create a neural network. Fig. 4 shows the data from the first quarter of 2016 [18] including the percentage share of theft of individual product groups and the average value of the stolen cargo. Based on this data and the probability of theft in road transport [19], the probability of a theft depending on the type of cargo was determined.

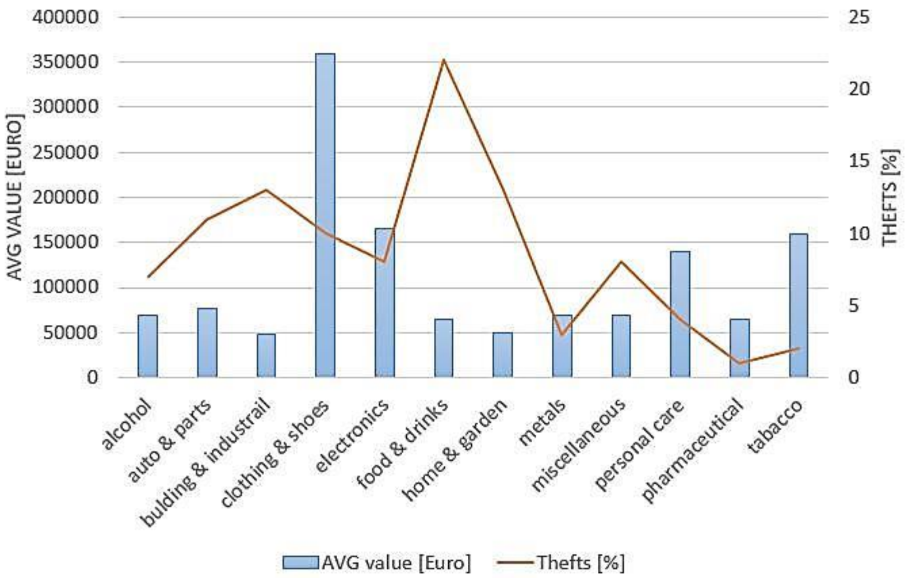


Fig. 4 Cargo theft by product type and value [18]

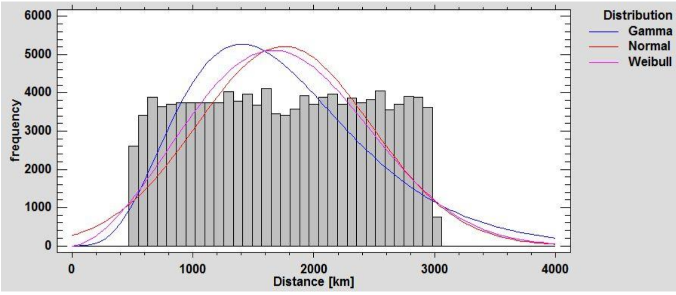
Other transport parameters such as transit time, distance, number of stops and type of semi-trailer were also generated. It was assumed that there was one stop for every 4.5 hours of driving, and the driving time was depended on the distance. The speed value for the distance below 1000 km was in the range of 30-60 km/h, while for the distance exceeding 1000 km the speed values were randomly generated from 60 to 80 km/h. Generally, 583350 cases were used for the learning process.

Then, in step II, the effect of the type of the carried cargo on the probability of theft was simulated. For this purpose, 10,000 transport cases, identical for each of the 12 types of cargo, were created. Based on the received data, it was possible to compare the impact of the cargo type on the probability of theft.

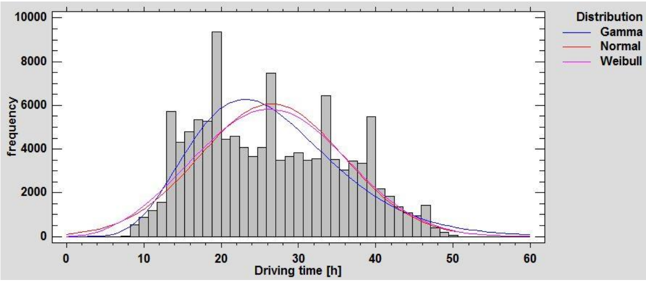
In step III, the costs of loss were calculated based on the appropriate algorithms. For variant I - a carriage without cargo monitoring systems and for variant II - a carriage with cargo monitoring systems, the cost of loss was calculated from Eq. (1).

5. Results

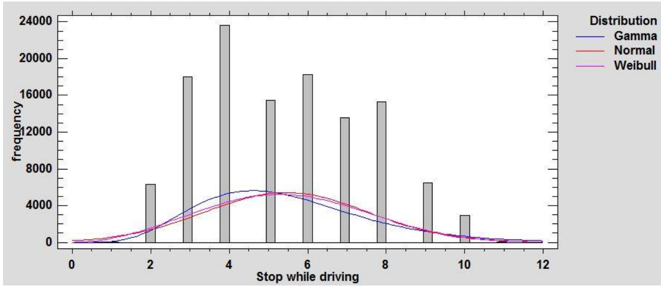
The statistical method was used to determine whether the type of cargo affected the probability of theft. A total of 120,000 simulations were carried out, 10,000 simulations for each type of the load. Each of these cases presented a different route of travel from 500 to 3,000 km (average distance 1,751 km), and a driving time was in the range from 8 to 50 hours (average 24.5 hours). The histogram of duration of transport is shown in Fig. 5. One to eleven stops were made during the transport. The simulation results are shown in Table 1 and Fig. 6. In Fig. 5, there are histograms for the distance, driving time and stops during driving. For each histogram, the Gamma, Normal and Weibull distributions were added.



(a) distance



(b) driving time



(c) stop while driving

Fig. 5 Histograms

Table 1 Summary statistics for probability of theft

Cargo type ID	Cargo type	Average	Standard deviation	Coeff. of variation	Maximum
1	alcohol	7.99E-12	8.50E-11	1063.69%	1.38E-09
2	auto & parts	1.83E-11	1.35E-10	738.41%	1.51E-09
3	bulding & industrial	0.00E+00	0.00E+00	0.00%	0.00E+00
4	clothing & shoes	3.95E-15	1.25E-13	3164.00%	8.92E-12
5	electronics	5.23E-12	9.05E-11	1730.30%	3.03E-09
6	food & drinks	2.67E-12	6.50E-11	2437.03%	2.81E-09
7	home & garden	3.77E-13	8.65E-12	2295.47%	4.18E-10
8	metals	2.85E-13	6.14E-12	2156.40%	2.38E-10
9	miscellaneous	4.80E-14	1.02E-12	2118.87%	3.79E-11
10	personal care	3.09E-15	1.39E-13	4513.09%	1.02E-11
11	pharmaceutical	5.35E-12	6.60E-11	1232.07%	1.42E-09
12	tobacco	0.00E+00	0.00E+00	0.00%	0.00E+00
Total	-	3.36E-12	5.97E-11	1777.70%	3.03E-09

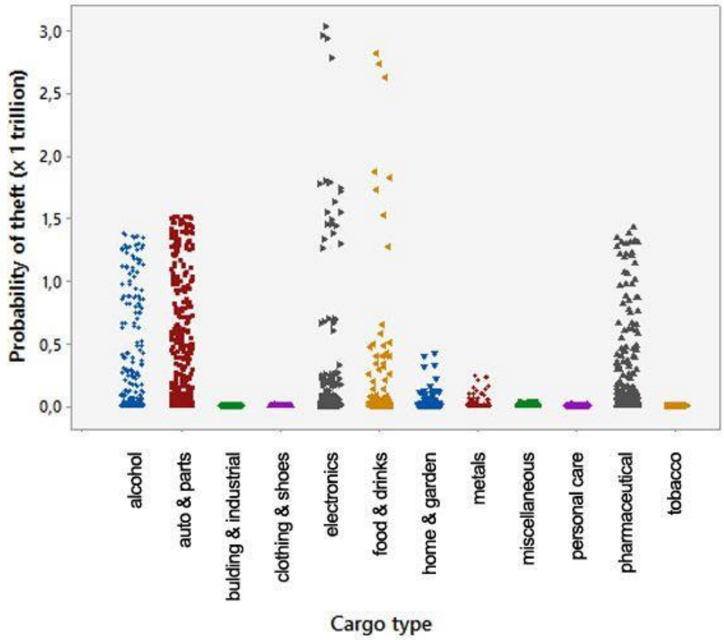


Fig. 6 Scatterplot of probability of theft vs cargo type

Table 2 ANOVA Table for probability of theft by cargo type

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Between groups	0,00000328282	11	2,9843E-13	84,37	0,0000
Within groups	0,000424422	119988	3,5372E-15	-	-
Total (Corr.)	0,000427705	119999	-	-	-

In order to check whether there is a statistical difference between the results obtained according to the type of cargo, the analysis of variance one-way ANOVA and Multiple Range Test were performed.

The ANOVA table (Table 2) decomposes the variance of the data into two components: a *between-group* component and a *within-group* component. The F-ratio, which in this case equals 84.3712, is a ratio of the between-group estimate to the within-group estimate. Since the P-value of the F-test is less than 0.05, there is a statistically significant difference between the means of the 12 variables at the 5% significance level. Due to these results, the Levene's Test was made. The test proved there are statistical differences between groups of products. The results of that test are presented in Table 3.

Table 3 Variance check by Levene's test

Comparison	Sigma1	Sigma2	F-Ratio	P-Value	Comparison	Sigma1	Sigma2	F-Ratio	P-Value
1 / 2	0,085	0,135	0,394	0,000	4 / 8	0,000	0,006	0,000	0,000
1 / 3	0,085	0,000	1,#INF	0,000	4 / 9	0,000	0,001	0,015	0,000
1 / 4	0,085	0,000	463355,000	0,000	4 / 10	0,000	0,000	0,802	0,000
1 / 5	0,085	0,090	0,883	0,000	4 / 11	0,000	0,066	0,000	0,000
1 / 6	0,085	0,065	1,709	0,000	4 / 12	0,000	0,000	1,#INF	0,000
1 / 7	0,085	0,009	96,685	0,000	5 / 6	0,090	0,065	1,936	0,000
1 / 8	0,085	0,006	191,736	0,000	5 / 7	0,090	0,009	109,505	0,000
1 / 9	0,085	0,001	6974,500	0,000	5 / 8	0,090	0,006	217,159	0,000
1 / 10	0,085	0,000	371723,000	0,000	5 / 9	0,090	0,001	7899,250	0,000
1 / 11	0,085	0,066	1,661	0,000	5 / 10	0,090	0,000	421010,000	0,000
1 / 12	0,085	0,000	1,#INF	0,000	5 / 11	0,090	0,066	1,881	0,000
2 / 3	0,135	0,000	1,#INF	0,000	5 / 12	0,090	0,000	1,#INF	0,000
2 / 4	0,135	0,000	1176040,000	0,000	6 / 7	0,065	0,009	56,559	0,000
2 / 5	0,135	0,090	2,241	0,000	6 / 8	0,065	0,006	112,162	0,000
2 / 6	0,135	0,065	4,339	0,000	6 / 9	0,065	0,001	4079,930	0,000
2 / 7	0,135	0,009	245,396	0,000	6 / 10	0,065	0,000	217450,000	0,000
2 / 8	0,135	0,006	486,645	0,000	6 / 11	0,065	0,066	0,972	0,151
2 / 9	0,135	0,001	17701,900	0,000	6 / 12	0,065	0,000	1,#INF	0,000
2 / 10	0,135	0,000	943468,000	0,000	7 / 8	0,009	0,006	1,983	0,000
2 / 11	0,135	0,066	4,216	0,000	7 / 9	0,009	0,001	72,136	0,000
2 / 12	0,135	0,000	1,#INF	0,000	7 / 10	0,009	0,000	3844,670	0,000
3 / 4	0,000	0,000	0,000	0,000	7 / 11	0,009	0,066	0,017	0,000
3 / 5	0,000	0,090	0,000	0,000	7 / 12	0,009	0,000	1,#INF	0,000
3 / 6	0,000	0,065	0,000	0,000	8 / 9	0,006	0,001	36,375	0,000
3 / 7	0,000	0,009	0,000	0,000	8 / 10	0,006	0,000	1938,720	0,000
3 / 8	0,000	0,006	0,000	0,000	8 / 11	0,006	0,066	0,009	0,000
3 / 9	0,000	0,001	0,000	0,000	8 / 12	0,006	0,000	1,#INF	0,000
3 / 10	0,000	0,000	0,000	0,000	9 / 10	0,001	0,000	53,298	0,000
3 / 11	0,000	0,066	0,000	0,000	9 / 11	0,001	0,066	0,000	0,000
3 / 12	0,000	0,000	-1,#INF	0,000	9 / 12	0,001	0,000	1,#INF	0,000
4 / 5	0,000	0,090	0,000	0,000	10 / 11	0,000	0,066	0,000	0,000
4 / 6	0,000	0,065	0,000	0,000	10 / 12	0,000	0,000	1,#INF	0,000
4 / 7	0,000	0,009	0,000	0,000	11 / 12	0,066	0,000	1,#INF	0,000

The table also shows a comparison of the standard deviations for each pair of samples. P-Values below 0.05, of which there are 64, indicate a statistically significant difference between the two sigmas at the 5% significance level. In Table 4, the homogeneity of variance done in the Multiple Rande Test is presented.

Table 3 applies a multiple comparison procedure to determine which means are significantly different from other differences. The method is currently used to discriminate among the means is Fisher's least significant difference (LSD) procedure. With this method, there is a 5.0% risk of calling each pair of means significantly different when the actual difference equals 0.

Statistical difference is found for the following product types:

1. alcohol (1)
2. auto & parts (2)
3. electronics (5), pharmaceutical (11)
4. food & drinks (6)

For other types, there is no statistical difference.

Table 4 Multiple range test for probability of theft by cargo type (Method: 95,0 percent LSD)

Cargo type ID	Cargo type	Mean	Homogeneous Groups
12	Tobacco	0,00E+00	X
3	Building & industrial	0,00E+00	X
10	Personal care	3,09E-15	X
4	Clothing & shoes	3,95E-15	X
9	Miscellaneous	4,80E-14	X
8	Metals	2,85E-13	X
7	Home & garden	3,77E-13	X
6	Food & drinks	2,67E-12	X
5	Electronics	5,23E-12	X
11	Pharmaceutical	5,35E-12	X
1	Alcohol	7,99E-12	X
2	Autos & parts	1,83E-11	X

6. Conclusions

The developed method allows one to determine the risk of cargo theft and related costs. In the presented example, transport factors such as the type of carried cargo, duration of transport, distance, number of stops and the type of semi-trailer have been taken into consideration. Therefore, other factors, such as the day of the week, the month, the state or the region of transport, may also be used as a learning data in the proposed method. The numbers of stops are one of the riskiest factors during transportation. However, the importance of the mentioned factors is always different for each company. That is why each company should use their own data from the completed transport to predict risk in the transportation process.

The presented results of the simulation confirm that alcohol, autos & parts, electronics, pharmaceuticals and food & drinks are cargos most exposed to theft. For these cargos, the forwarders should consider the use of special systems to monitor cargo parameters and location. For other types of goods, there are no statistical differences in a probability of theft, and the risk is relatively low. Therefore, if the distance of transportation is rather small and the number of stops is low, it will not be profitable to use additional systems to lower the risk. This would be unnecessary cost. The Information about the parameters of transportation, the rates given in contract, the type of cargo, and the information about risk, which appears or not, are the basic data for risk prediction. The method presented by the authors was developed to avoid this situation.

The proposed method helps to predict a typical risk in transportation, but there may be some disruption hard to predict. The disruption may include earthquakes, hurricanes, accidents, strikes, terrorism and more. To predict those incidents a similar method can be used, but it requires many types of data from different information sources. That is why those systems must use, for instance, the BigData analysis and artificial intelligence tools to be able to select important data, transform them and treat by compound algorithms in the real time. The authors hope to have made their contribution in the area of risk prediction methods which are dedicated for each company. Due to that, the proposed method can be used to develop software that allows the engineers to calculate premium rates in the case of increased risk.

In the future, the authors intend to conduct the sensitivity analysis in order to examine the influence of the input parameters on the variance in the output probability. The development of this software is planned for the next stage of research.

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