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Data-driven analysis of the airport cargo screening process

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Shipments transported by air are screened, as are passengers and their luggage. It aims to detect objects or substances that can be used to commit an act of unlawful interference. New equipment and control techniques are often introduced into widespread use. Therefore, studying the effects of using them for the cargo security checkpoint (CSC) is essential. The screening process is complex, and its parameterization under specific conditions is challenging. The research aimed to analyze the security screening process, considering the number of items included in a single load and its weight. The main focus of the study was on the CSC throughput, depending on the type of shipment being inspected. The results of 2021 measurements were used, which recorded the type and time of inspection performed. A model based on a Bayesian Network was developed to examine the probability of running particular types of checks. An essential part of the research was developing a tool for predicting the inspection time of an entire batch of shipments to be transported on a single flight. For this purpose, a Naive Bayes Classifier was used, which proved effective in the application studied. The methods used, and the tools created made it possible to evaluate different variants of CSC equipment for the screening process in terms of throughput.

Keywords: Security screening, Bayesian network, air transport, safety and security, aviation cargo, critical infrastructure protection.

1. Introduction

Shipments transported by air are screened, as are passengers and their luggage. It aims to detect objects or substances that can be used to commit an act of unlawful interference. International regulations govern them, while their implementation is monitored due to the possible severe consequences of allowing prohibited substances to be transported. These regulations are subject to frequent amendments aimed at the mandatory introduction of increasingly newer equipment and control techniques into widespread use. The modifications are necessary due to the parallel development of methods and techniques used by those planning to commit an act of unlawful interference. Therefore, it is essential to study the effects of using the aforementioned new equipment variants for the cargo security checkpoint (CSC) and new inspection procedures. The two most vital criteria in this evaluation are the effectiveness of detecting prohibited items and substances and the capacity of the CSC. These criteria are contradictory, which forces the search for compromise solutions.

The organization of the cargo screening system is often inadequate to meet the demand determined by the volume of freight handled. This applies to all stages of screening. Often redundant solutions are used, which are justified by the constant increase in the volume of air traffic. However, there are then high costs of operating the system. In addition, it usually takes several years to reach the target level of traffic, at which point the equipment used may become obsolete, and replacement may be required.

On the other hand, there is often a situation where the capacity of the cargo screening system is insufficient. Then it is necessary to expand the inspection system. In addition, this state of affairs is also influenced by the systematic annual increase in freight, which undoubtedly reflects the increase in public demand for air transport.

Carriage of cargo by air is characterized by a rather complicated process related to the acceptance of goods for transport and their appropriate preparation for carriage on board an aircraft. Following current regulations (European Commission, 2015), these tasks are performed by a registered agent, who is also responsible for implementing cargo screening. This control is carried out by qualified security personnel - security screening operators (SSOs). These individuals have been certified by the Civil Aviation Authority (CAA) after a series of time-consuming training courses and passing a state exam.

According to the current civil aviation security regulations, the following are prohibited for carriage in cargo: assembled incendiary and explosive devices not carried following the applicable security rules. It is, therefore, the duty of the screening operator to exercise due diligence to ensure the safety of the air operation being performed. They have equipment dedicated to detecting prohibited items and substances at their disposal. The primary and most common device is the X-ray scanner. Other frequently used devices include ETD, used to detect explosive materials or their residues on surfaces, objects, or people. ETDs work by analyzing samples collected from the surface or air using various techniques, such as ion mobility spectrometry, mass spectrometry, or colorimetry.

The security screening operator can also verify the cargo's contents by performing a manual inspection. It is a time-consuming activity due to the need to break down the load into individual pieces. Visual inspection with other inspection methods should also be distinguished from a manual check. However, a visual inspection can be used only in cases where the nature of the cargo (its composition and structure) allows it.

2. State of the Research

Previous research has created several models to study the capacity of the screening system for passengers and checked and cabin baggage (Skorupski et al., 2018; AlKheder et al., 2019; Li et al., 2018; Mota et al., 2021). A separate group of works dealt with the analysis of the effectiveness of such inspections (Skorupski and Uchronski, 2018), including taking into account the human factor (Knol et al., 2019; Skorupski and Uchronski, 2015; Michel et al., 2014) and also the relationship between throughput and effectiveness (Lee and Jacobson, 2011). In addition to these two criteria, some researchers proposed costs for evaluating security control systems (Kirschenbaum, 2013; da Cunha et al., 2017; Gillen and Morrison, 2015). The extent of automation in airport security screening and the impact of technical equipment on its effectiveness is also present in the literature (Leone and Liu, 2005; Huegli et al., 2020; Skorupski and Uchronski, 2020).

As already mentioned, air cargo security screening is governed by numerous international regulations. Domingues et al. (2014) and Price and Forrest (2016) analyzed policies in this regard. Risk-based security screening concept was studied by Wong and Brooks (2015)

An analysis of the literature, necessarily presented here very briefly, clearly shows that the most common approach is based on models examining the physical relationships between elements of a security control system. What is lacking, however, is an approach that uses data-driven models. It indicates that there is a research gap that we plan to fill, and our first attempt to do so is through this article.

3. Research Problem

Due to the possible wide variety of shipments, the screening process is complex, and its parametrization under specific conditions is challenging. The research aimed to analyze the cargo security screening process, considering the number of items included in a single load and its weight. In doing so, it should be noted that these shipments are usually commercial and must be delivered to a specific consignee quickly and intact. It necessitates a particular approach to the inspection process, which seeks to preserve the integrity of each shipment. If operational inspection of a shipment's contents requires disassembly, it is necessary to reintegrate it into the original cargo unit. This makes the inspection process time-consuming, a significant problem in on-time delivery. Punctuality is critical because most cargo shipments are transported by aircraft also carrying passengers and their luggage.

Two major problems are apparent when organizing the cargo screening process. Both are related to estimating the time reserved for inspecting shipments that will be transported on a given flight. In doing so, having an exact value of this time is not essential, but only to qualify it into one of several ranges: short, medium, long, or very long.

The first problem is the proper organization of the checkpoint. It is necessary to provide adequate technical equipment and staffing of inspection operators to ensure sufficient throughput to handle the anticipated traffic. The works undertaken in this article will support the solution to this problem in practice. They were started in connection with the need to decide on the type of X-ray machine used for screening shipments. Several types are commercially available, differing in, among other things, the size of the inspection tunnel and the ability to penetrate deep into the cargo. An example device is shown in Figure 1.

Fig 1. Example of an X-ray device for screening cargo shipments (Smiths Detection, 2021)

The general idea behind this type of equipment is to inspect the entire pallet containing the cargo, as shown schematically in Figure 1. However, shipments are not always delivered in this form by the shipper, and adequate preparation is necessary. On the other hand, a load integrated into a pallet often prevents it from being wholly penetrated by X-rays. In this case, it is necessary to disassemble the shipment and, after inspection, reassemble it to its original form. Of course, the size of the inspection tunnel and the ability for deeper penetration (offered by some X-ray equipment) reduce the likelihood of this necessity.

The abovementioned problems highlight the second major problem needed to be solved by cargo screening services and the second motive for undertaking the research, the preliminary results of which are presented in this article. It is the question of the organization of the inspection process itself, particularly determining the time necessary for its implementation. Starting the inspection at the wrong time can lead to delays in the shipment delivery or organizational problems at the airport, for example, storage-related issues.

Cargo shipments scheduled to be transported on a single aircraft are generally collected for a certain period before the flight and stored in a separate area. Then, they are inspected collectively shortly before their scheduled departure and packed onto the aircraft immediately afterward. A marked difference can be seen here from the inspection of passenger baggage, which is inspected as passengers arrive and then sorted into the appropriate aircraft. In the case of cargo, this is not possible, as shippers deliver shipments at different times, including well before scheduled departure. Given such cargo preparation technology, estimating the time required for inspection is very important. Some guidance is provided by the available information on the shipment's contents. However, it is general and does not allow for a precise determination of both the type of inspection needed and the time required.

One way to solve this problem is through analysis using data. It will be possible to estimate better the right moment at which the inspection should be initiated by having measurements that specify the type of inspection performed, but also the weight of the shipments and the number of pieces that comprise them, as well as the time that was required to complete the inspection,

4. Model of Cargo Screening Process

The main focus of the research was on the CSC throughput, depending on the type of shipment being inspected. The results of 2021 measurements conducted at Katowice International Airport (ICAO code EPKT) were used for this. We recorded the duration of the inspection, the number of loads comprising one shipment, the weight of the shipment, and the detailed inspection procedure. An example excerpt of the collected data is shown in Table 1. The following control patterns were identified:

- XRY - a single X-ray screening with an X-ray device, as a result of which the operator was able to determine whether the cargo could be allowed to be transported,
- XRY+XRY - double screening used when the density or nature of the load prevents a proper assessment of its contents (so-called black

alert), and it is necessary to perform an inspection from another angle or after the shipment has been decomposed,

- ETD, VCK, or PHS - a single inspection using an explosive trace detection device (ETD), visual inspection (VCK), or manual inspection (PHS) - typically used when the load is too large to be placed in an X-ray machine,
- XRY+ETD - two-stage inspection, used after a black alert, consisting of X-ray screening in an X-ray machine followed by check by detecting trace amounts of explosives; alternatively, XRY+PHS or XRY+VCK were used,
- a combination of ETD, VCK, and PHS methods.

Table 1. Example of raw measurement data (excerpt)

Inspection start	Inspection end	Pieces	Weight	Control method
20:04:23	20:50:53	16	7045	XRY
21:06:40	21:07:01	1	133	XRY/ETD
21:08:23	21:08:42	1	53	PHS/ETD
22:21:57	22:22:13	40	4170	VCK
23:37:23	23:37:38	8	643	XRY
23:38:04	23:38:22	1	17	XRY

A model based on a Bayesian Network (BN) was developed to examine the probability of performing particular types of inspections depending on the weight and number of pieces comprising a single cargo unit and the execution times of inspection procedures. A schema of this model is shown in Figure 2.

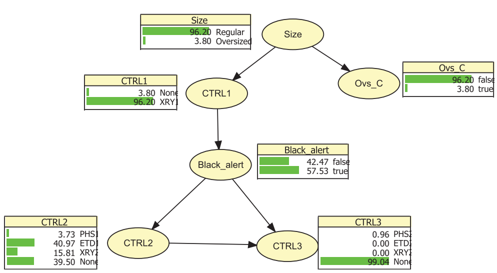

Fig 2. Schematic of cargo security screening model using Bayesian network

The *Size* node represents the check to see if there is an oversize load. The *CTRL1*, *CRTL2*, and *CTRL3* nodes represent the subsequent inspection steps. The Black alert node represents the situation when the cargo cannot be classified as safe after the first inspection with the X-ray machine. The *Ovs_C* node represents the inspection procedure implemented for oversized freight. The monitors shown in Figure 2 next to the nodes illustrate the apriori conditional probabilities of specific control steps occurring, determined from measurements.

The diagram shown in Figure 2 corresponds to measurements made using an older generation device with a smaller inspection tunnel diameter and less capacity to penetrate deep into the cargo. Analogous measurements taken when using other X-ray equipment (with a larger inspection tunnel diameter and better cargo penetration capability) will show different probabilities of both needing to decompose the cargo and performing particular types of inspections.

A data-driven model of the cargo screening process was developed in the HUGIN Researcher package (Madsen et al., 2003; 2005; Bromley et al., 2004). This package was also used to create a Naïve Bayes classifier and conduct analyses using it (Section 5). HUGIN Researcher Software is a tool for building and analyzing Bayesian networks (BNs). Using a graph structure, BN is a statistical model representing the dependencies between random variables. HUGIN Researcher Software offers a user-friendly graphical interface for constructing, testing and refining BNs. It supports a variety of probabilistic inference algorithms, including exact inference, approximate inference, and sampling-based methods. In addition, HUGIN Researcher Software provides tools for learning the structure of a BN from data, known as structure learning, and for estimating the parameters of a model, known as parameter learning. HUGIN Researcher Software has applications in various fields, including healthcare, finance, risk assessment, and predictive modeling. Researchers and practitioners widely use it for decision-making, prediction, and diagnosis.

5. Naïve Bayes Classifier Model Results

An essential part of the research was developing a tool for predicting the inspection time of an entire batch of shipments to be transported on a single flight. For this purpose, a Naive Bayes Classifier was used, which proved effective in the application studied (Kjaerulff and Madsen, 2013).

The Naive Bayes Classifier is a simple but effective probabilistic classifier based on Bayes' theorem, which states that the probability of a hypothesis or event given some observed evidence is proportional to the likelihood of the evidence given the hypothesis, multiplied by the prior probability of the hypothesis:

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \quad (1)$$

where

A, B – events, $P(B) > 0$,

$P(A|B)$ – the probability of occurrence of an event A provided that event B occurs,

$P(B|A)$ – the probability of occurrence of an event B provided that event A occurs,

The Naive Bayes Classifier assumes a data point's features (or attributes) are conditionally independent given the class label. Given the class label, the presence or absence of a particular feature does not affect the probability of other features being present or absent.

Despite its simplifying assumption, the Naive Bayes Classifier can be effective in practice, especially when the number of features is large and the amount of labeled training data is limited. It is widely used in text classification, spam filtering, sentiment analysis, and other applications. It is also possible to use the Bayes Classifier to predict the time of cargo shipment screening concerning the weight of a load and the number of pieces.

An example of the structure of a model directed at estimating the time required to perform a shipment inspection is shown in Figure 3. In addition to the different types of checks discussed earlier, it also considers the number of pieces in shipment and their weight.

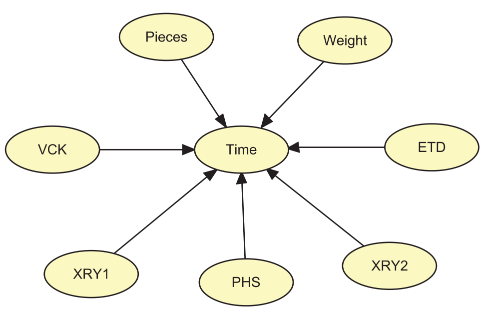

Fig 3. Structure of the Naive Bayes Classifier model (VCK – visual inspection, XRY – X-ray screening, PHS – manual inspection, ETD – explosive trace detection)

The Bayesian network used for prediction was subjected to a learning process. A learning sample was created from a portion of the data. The data, the structure of which is described in Section 4, was collected during one month of 2021. It included 534 inspected shipments. Of these, 356 were randomly selected, and a learning sample was created, representing about 2/3 of the total data. It was then subjected to the discretization of the values of nodes and then used to create a classifier whose primary purpose was to estimate the time of security checks by calculating the conditional probability distributions of the screening time given the weight and number of pieces of a shipment. This time depends on the inspection carried out, which depends on the cargo weight and the number of pieces. The computational cost of the data fitting process is small; it did not exceed one minute for our data set.

Once the classifier has been trained, we used it to predict the screening time of new shipments based on their weight and number of pieces. Of course, the problem formulation of the Naive Bayes is a classification problem. So, our goal is not to predict the exact value of the control time but to classify it into a particular type class: short, medium, long, and very long. It is sufficient to achieve the practical goals we indicated earlier. We compared the test set's expected and actual screening times to evaluate the classifier's performance. We used a test sample comprising the remaining 1/3 of the collected measurement data. For example, Fig. 4 shows the quality of the created classifier to predict the performance of ETD control. It was assessed using a ROC curve.

The ROC (Receiver Operating Characteristic) curve is a graphical representation of the performance of a binary classification model. It plots the true positive rate (TPR) against the false positive rate (FPR) at various classification thresholds. The TPR is the proportion of actual positive cases correctly identified as positive by the model. At the same time, the FPR is the proportion of actual negative cases incorrectly classified as positive by the model. The ROC curve is created by calculating the TPR and FPR for different threshold values, ranging from 0 to 1, and plotting the results on a graph. The area under the ROC curve (AUC) is often used as a summary statistic for the performance of a classifier, with higher values indicating better performance. AUC ranges from 0 to 1, with a value of 0.5 indicating that the classifier performs no better than chance. Good compliance was obtained in our case, allowing the proposed classifier to be used in practice. However, the prediction accuracy may depend on various factors – the quality of the data, the choice of classifier, and the complexity of the relationship between the input variables and the output variable.

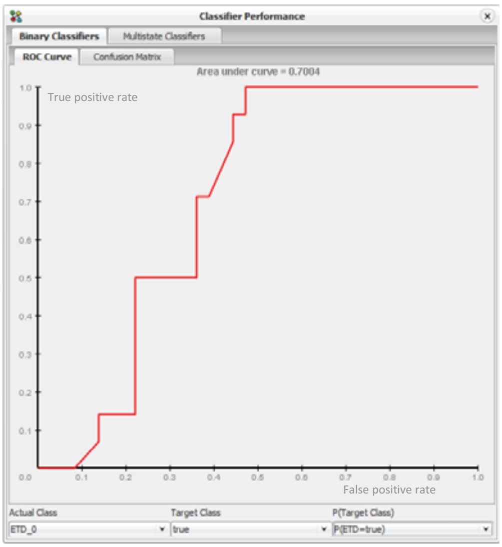

Fig 4. Performance of ETD control execution prediction using the created classifier

In further work, we plan to look for even better variants of the classifier, taking into account other structures of the model (other relationships between data) and new measurements carried out, taking into account other organizations of the cargo security checkpoint. An example of such a change could be the combined treatment of manual and visual inspection, which are formally different but, in practice, are used in similar situations and take similar time.

Of course, as stated earlier, our primary goal is to forecast cargo screening time, which is not binary. For it, it is necessary to use other methods to verify the quality of the forecast. Work in this area is ongoing, but the results are very promising.

6. Conclusions

The developed model served to understand better the course of the cargo screening process at the airport. In particular, the probabilities of performing each control sequence were quantified as a function of the weight and number of pieces comprising a single shipment. These results will form the basis for determining the parameters of the micro-scale simulation model of the studied process, which is planned to implement in the form of a colored, timed, stochastic Petri net. These probabilities depend on several factors. One of the most important, which motivated the study, is the choice of X-ray equipment for inspecting cargo shipments. Another, equally important, is the type of cargo. It is determined at the initial observation by the SSO. It is the basis for deciding whether additional inspections are necessary or even replacing the X-ray device inspection with other types. This type of decision is subjective and is not reflected in the data acquired for the study. It is, therefore, necessary to continue the study considering this factor, among others.

The research showed a specific type of hierarchical control structure and a certain dependence of the control methods on the number of pieces and shipment weight. This observation will be the starting point for further research, in which we plan to consider other structures of the data dependency model and different classifiers. Comparing these variants should lead to finding an effective and efficient tool for estimating cargo screening time. At this preliminary stage of the research, however, it can be concluded that the data-driven models appear very promising for application in the area under discussion.

The method used, and the tool created made it possible to evaluate different variants of CSC equipment and other solutions for the screening process in terms of throughput. They thus provided the basis for the bicriteria analysis mentioned earlier. In particular, the impact of using a new X-ray device with greater penetration capacity deep into the cargo and a larger inspection tunnel was studied. In such a situation, we less often have to treat the load as oversized, and black alert situations are also less frequent. It allows for greater throughput of the security inspection system, which is extremely important for airport operations.

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