

Risk-based Customs' Intrusive Inspection Decision Making: Algorithm & Preliminary Case study

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Abstract

This work is carried on within the frame of the EU Horizon project “BAG-INTEL”. The BAG-INTEL project final target is to develop a Risk-based AI tool to support customs intrusive inspection decision making relative to luggage control in airports. The risk assessment component is the only component of the BAG-INTEL Tool that is presented in the paper. The risk assessment component is one of many other components to be developed in BAG-INTEL Tool. It is powered by an algorithm mixes probabilistic statistics (deductive approach) and Analytic Hierarchic Process (AHP) classification theory (inductive approach). Subsequently, the risk assessment algorithm does not exploit any AI methodology or facility. The exploited data are exclusively numerical figures. Hence, the risk assessment algorithm does neither retrieve nor process any personal or biometric data by its concept.

Two risks are identified and assessed. The first is to miss a bag containing illegal substances (detection failure). The second is to intrusively inspect a clean bag (false detection). We consider three individual risk indicators to estimate the likelihood of illegal substances in a bag: external-intelligence informative risk indicator, sniffer dog risk indicator, and X-scan risk indicator. The list of searched illegal substances of interest is purposely limited to narcotics, tabaco, currency notes, gold, and polymers. The individual risk indicators should be aggregated to determine one global risk indicators by the risk assessment algorithm presented in the paper.

The mathematical models used are briefly presented and applied using academic data simulating the three risk indicators cited above. The paper presents the state of progress in the development of the risk assessment algorithm and the results of its preliminary numerical testing.

The paper is intended to be didactic and accessible to Customs Inspection Decision Making professionals as far as the the probabilistic risk assessment concept and the related algorithm are concerned.

1 Introduction

This work is carried on within the frame of the EU Horizon project “BAG-INTEL”. The BAG-INTEL project’s final target is to develop a Risk-based AI Tool (RBIT) to support customs decision making relative to luggage intrusive inspection in airports. The Risk-Assessment Algorithm (RAA) is developed and is in the pre-testing phase. It is one of the BAG-INTEL Tool’s components. It is not an AI algorithm and does neither exploit nor process any personal or biometric data. It exploits exclusively numerical data and is based on classical probabilistic and statistic risk assessment approaches.

The paper focuses on the algorithm and the implemented mathematical models that process the data concerning the identified risks. The different features of the risk assessment methodology are illustrated and presented through an academic case study. The case study exploits customs inspection experience feedback data and practices. But the individual risk indicators data used are simulated ones as explained later. The simulated data are the external-intelligence informative risk indicator, sniffer dog risk indicator, the X-scan risk indicator, and the bag camera identification and re-identification matching indicator.

The algorithmic concept presented in the paper is based on an upgraded methodology combining applied statics’ techniques, probability theory, and Analytical Hierarchical Processing method (AHP). The combination of these techniques was not indeed a free choice of the authors. It was rather a practical processing necessity as the used data are of different categories: probabilistic expectations, objective statistical observations, and customs’ inspection cumulated subjective numerical scoring.

The concerned risks in the case study are:

- The risk of “false detection, FD”; when customs’ officers decide to intrusively inspect a bag and find no illegal substances. This action is wasting time and consuming resources with no-profit outcome.
- The risk of a “detection failure, DF”; when customs’ officers decide not to inspect a bag containing illegal substances because nothing is detected. This is a potential tax loss and a breach in crime fighting efforts.

Obviously, one should minimise the above risks exposure in bags inspection practices. This should be carried on using a “risk-based inspection decision making” process as recommended by the World Customs Organisation (WCO) guides and the EU directives and strategic progress monitoring reports regularly addressed to the EU decision makers & parliament.

The method used in the realisation of this task of the BAG-INTEL project is presented in section 2, below.

2 Why and How - The Method

The authors have, first, to identify why the EU and the international “concerned” community emphasis on introducing risk assessment in luggage inspection decision making process. A brief screening of the EU and International context of customs practices is presented in section 3. This is necessary to identify exactly the kind of risks to be included in the risk assessment.

In section 4, the authors specify the risks that should be assessed within the context of the “luggage intrusive inspection” by customs, in airports. Once the risks are fully specified, the authors should look at the identification of the required relevant data issues, their availability and their accessibility.

In section 5, the required data, data sources, their availability and their accessibility are identified. A brief presentation is then given. The identification of the risk assessment inputs and outcomes is also carried on. They are specified in the form of individual risk indicators and a global risk indicator to be determined, respectively. The input data and the outcome of the risk assessment are all numerical data. No meta-data, personal data or biometric data are involved in the risk assessment data processing.

Section 6 treats the “Inspection Experience Feedback” as perceived by the customs partners participating in the BAG-INTEL project. The “Customs’ Inspection Experience feedback” data is formulated by an effectiveness rate of the intrusive inspections and a trustworthiness level that customs allocate to each individual risk indicator. The trustworthiness score goes from 1 to 10, where 10 is the highest trustworthiness level. This dataset allows to weight the relative effectiveness of the individual risk indicators.

Section 7 gives details on the individual risk indicators and their aggregation in a global risk indicator. It treats the relative weighting of each individual risk indicator as their contributions are not equal. The weighting factors are deduced thanks to the “Inspection Experience Feedback” data detailed above in section 6.

Section 8 presents the aggregation algorithm of the weighted individual risk indicators to determine the global risk indicator. This is the main subject of the paper, the algorithm concept, its numerical input data, and its numerical outputs. After the numerical validation of the algorithm, it is supposed to be implemented in the BAG-INTEL Decision-Making Support Tool that is build-up of many other modular algorithms and components. The risk assessment algorithm discussed in the paper is not an AI-algorithm.

An academic case study is detailed in section 9. It should validate the principal of the algorithm that aggregates the individual risk indicators, considering their individual weights based on customs’ inspection experience feedback. The input individual indicators should be provided by other algorithms and components external to the BAG-INTEL Tool. These are: External & Intelligence Risk Indicator, Sniffer Dog Risk Indicator, X-scan Data Risk Indicator, Camera Identification/Re-identification Risk Indicator. The numerical validation of the Risk Assessment Algorithm is then carried on using simulated individual risk indicators. For the purpose the academic case, the risk indicators have been simulated.

Section 10 presents the conclusions of the case study relative to the numerical validation of the Risk Assessment Algorithm.

3 EU and International Context

The WCO recommends that intrusive customs inspections should be limited. A Risk Management Guide has been developed by the WCO, (WCO, 2003). The WCO defines risk management as “the systematic determination of

risk management priorities by evaluating and comparing the level of risk against predetermined standards, target risk-levels or other criteria”, as quoted in the WCO (2003b) guide.

In line with WCO recommendations, the European Commission released a Communication on the EU Strategy and Action Plan for customs risk management titled ‘Tackling risks, strengthening supply chain security and facilitating trade, on 21 August 2014 (COM-2014 527 final [2] and COM-2014 527 final-Annexe-1 [3]). In this founding communication, EU defines its strategic targets and the related action plan as following (citing):

- Improve data quality and filing arrangements
- Ensure availability of supply chain data and sharing of risk relevant information among customs authorities
- Implement control and risk mitigation measures where required
- Strengthen capacities
- Promote interagency cooperation and information-sharing between customs and other authorities at the Member State and EU level
- Enhance cooperation with trade
- Tap the potential of international customs co-operation

A detailed EU action plan is given in (COM – 2014 527 final-Annexe1) mentioned above. Three monitoring progress reports on “the Implementation of the EU Strategy and Action Plan for Customs Risk Management” have been published regarding the COM – 2014 527, in 2016 (1st Prog Rep, 2016), 2018 (2nd Prog Rep, 2016), and 2021 (3rd Prog Rep, 2016). The EU Court of Auditors has conducted an interesting special audit and published a report (Special Report, 2021) entitled “Customs controls: insufficient harmonisation hampers EU financial interests” that focused only on the Financial Risk Criteria (FRC). Still, it sheds an intensive light on the fact that both interconnected customs’ missions, financial and law enforcement, should follow risk based decision making process.

4 Risks Identification

As mentioned briefly above, the BAG-INTEL project (HORIZON-RIA, 2023) focuses on the risks that hamper the “Inspection Process Efficiency”, in EU-airports.

The risk inspection process may be hampered, Figure 1, by:

- Either the “detection failure” of illegal substances (DF – detection failure),
- Or the “false detection” of illegal substances (FD – false detection)

Both “detection failure” and “false detections” risks contribute to lowering the performance of the Customs’ Control Process. Both risks should be managed taking advantage of the advanced non-intrusive detection technologies.

Figure 1 presents schematically the four possible scenarios, regarding a bag that went through a detection system:

FC: Free of illegal substances and detection confirms

FD: Free of illegal substances but false detection occurs

DF: Illegal substance exists but detection system fails

DC: Illegal substance exists, and detection system confirms

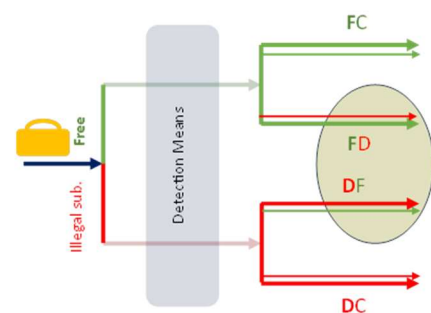


Figure 1: Schematic presentation of risks

5 Data Identification

Data retrieval relative to illegal trafficking is a complex process that depends on two different types of data retrieval mean: soft and hard ones. Soft data-retrieval covers the use of all relevant data and knowledge assets regarding the concerned illegal activities. Most of these assets are government-owned, private and with no

public-access. The hard means cover all relevant remote sensing and scanning engineering technologies. Both require the use of a wide spectrum of data collection, processing, and aggregation advanced technologies.

Within BAG-INTEL project's perspective, the relevant knowledge & data sources are supposed to include:

Potential external sources of risk data

1. Flight data (itinerary, ticket, airline, payment)
2. Pax data (records, personal data, luggage)
3. LEAs data bases (INTERPOL, EUROPOL, SIS II)
4. Risk information forms – RIF (Within the frame of CRMS2)
5. World Customs Organisation (WCO) annual Illicit Trade Intelligence Report

Internal sources of risk data (to store the numerical outputs of the Risk Assessment Algorithm)

6. Customs inspection experience feedback database

Remote sensing equipment and scanning technologies:

7. Sniffer dog
8. X-scan imaging
9. Camera bag-identification (at the entrance of the X-scanner)
10. Camera bag-reidentification (in the customs control zone)

Each of the above ten sources of knowledge & data contributes to the evaluation of the global risk level. Each contribution is determined by an appropriate Individual Risk Indicator (IRI). A Global Risk Indicator (GRI) should be determined by the aggregation of the IRI's, mentioned above.

Knowledge & data sources N°1 to N°5 should be aggregated together to produce only one IRI. It is called external-intelligence risk indicator (I_e). Given the purpose of the case study, the value of the external intelligence risk indicator (I_e) will be simulated. The risk assessment algorithm is not conceived to process the data contents in the databases from N°1 to N°5.

The X-scan risk indicator (I_x), the camera identification indicator (I_{c1}) and the camera reidentification indicators (I_{c2}) are directly determined by the algorithms of the scanning machine and the cameras and supplied to the risk assessment algorithm.

While, The Global Risk Indicator "GRI" (I_G) will be determined by the aggregation of the external intelligence risk indicator (I_e), the sniffer dog (I_d), the X-scan (I_x), the camera identification indicator (I_{c1}) and the camera reidentification indicators (I_{c2}). The BAG-INTEL data flow diagram is schematically presented in Figure 2 below.

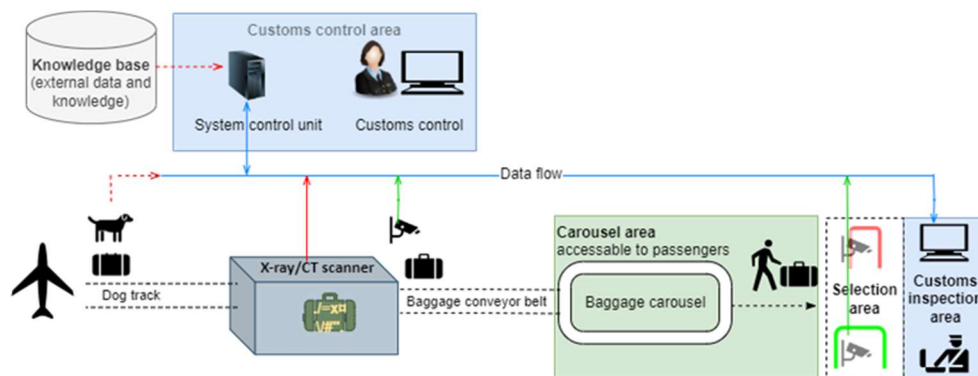


Figure 2: Schematic presentation of BAG-INTEL Data Flow
source reference: (HORIZON-RIA, 2023)

The unique function of the risk assessment algorithm is the aggregation of all individual risk indicators to determine the Global Risk Indicator (I_G).

Still to specify the “Customs inspection experience feedback knowledge”. Such database does not exist (yet) amongst the LEA’s databases assets or in the relevant literature, as far as the authors can tell. A local “Customs inspection experience feedback knowledge” data base is built up. It exploits the local inspection experience feedback of the BAG-INTEL customs’ partners, as described in the following section.

6 Inspection Experience Feedback

Why is the “Customs inspection experience feedback knowledge” important?

To get a representative overview about the trustworthiness level that customs officers give to the individual risk indicators as function of the searched contraband and vis-versa, a questionnaire has been developed and send to the customs organisation that participate in BAG-INTEL project consortium.

The 1st part of the questionnaire, Table 1, has permitted to estimate the success rate in intercepting contrabands in two configurations: 1) risk assessment-based inspection and 2) random or behaviour-based inspection.

Table 1 : Questionnaire – 1st part

Give, roughly, the total number of the inspections you carried on over a defined time-interval* T : -----
** A time-interval that represents roughly your operational experience in luggage inspection activities.*

What is the interval T (in Years) you are considering?

$0 < T \ll 1$ ☐ less than or equal to 1 year
 $1 < T \ll 5$ ☐ longer than 1 year but less than or equal to 5 years
 $5 < T \ll 10$ ☐ longer than 5 years but less than or equal to 10 years
 $10 < T$ ☐ longer than 10 years

Considering the total number of inspections mentioned above, what are the ratio (%) of:

The risk-based inspections -----%
 The behaviour-based inspections (if you have a “Behaviour Detection Programme”) -----%
 The random-based inspections (if you have a Random Inspection Protocol) -----%

Considering the inspection categories mentioned above, give the ratios (%) of full success¹, partial success² and unsuccess³ per each inspection category in Table 1, below:

Table 1: Ratios (%) of full success¹, partial success² and unsuccess³ per each inspection category

Inspections Category	Full Success ¹	Partial Success ²	Unsuccess ³
Considering only the “Risk-Based Inspection”%%%
Considering only the “Behaviour-Based Inspection”%%%
Considering only the “Random-Based Inspections” ⁴%	0%%

¹ The expected contraband is found.
² A contraband is found but not the expected one.
³ No contraband is found.
⁴ In random-based inspection “partial” successes has no sense, as no specific contraband is expected. You have only 2 options: “full success” if “a contraband” is found or “unsuccess” if no contraband is found.

The 2nd part of the questionnaire, Table 2, has been developed and proposed to all BAG-INTEL customs partners. The customs partners were asked to score twice, from 0 to 10 using Table 1, according to two different point of views.

From point of view – 1, the customs officer scores column-by-column (i.e. per illegal substance) the relative trustworthiness level given per type of risk data source, according to his/her cumulated inspection experience.

From point of view – 2, the customs officer scores line-by-line (i.e. per risk data source) the relative trustworthiness level given per type of illegal substance, according to his/her cumulated inspection experience.

The list of searched illegal substances was purposely limited to narcotics, tabaco, currencies, gold and polymers. The extension of the searched illegal substances is straightforward if a wider spectrum of illegal substances is required. No limitations are imposed by the risk assessment algorithm on the number of the illegal substances.

The metrics used to score the Customs' trustworthiness level in risk data sources as function of illegal substance varies from 0 to 10. The transfer grid between different scaling systems: discrete figures (0 to 10), and continuous probabilistic figures, is indicated in table 2 below.

Table 2: Questionnaire 2nd part – Trustworthiness level – Risk Data Sources v.s. Detected Illegal substances

Risk Data Sources	Narcotics	Tabacos	Currency	Gold	Polymers
Intelligence & Knowledge Databases					
Dog detection capability					
X-scanning					
Luggage photo identification					
Luggage photo re-identification indicator					

Table 2: Equivalence grid of different scoring scales

	Score ¹	Qualitative scale	Probability scale	
1	0-2	Very Low	0 – 20%	
2	3-4	Low	20 – 40%	
3	5	Medium	40 – 60%	
4	6-7	High	60 – 80%	
5	8-10	Very High	80 – 100%	

¹ is used for scoring in the tables when collecting the customs inspection experience feedback

Processing the trustworthiness levels according to the operational inspection experience of the customs officers will provide the relative weighting figures of the individual risk indicators. The relative weighting figures are necessary for a meaningful aggregation of different individual risk indicator to produce the global Risk indicator.

The customs inspection experience feedback local database is still in construction. BAG-INTEL has collected (up to date) some 60 answer sheets cumulating more than 500000 inspection acts. The final statistical processing of all the collected data is expected by July-August 2025.

All the collected data are exclusively numerical. Neither personal nor biometric data are collected.

7 Risk Indicators Weighing Process

The statistical weighting process is a statistical direct application on the trustworthiness scoring of each customs officer. Thanks to the scoring of each customs officer, we could determine mean values representing the trustworthiness of the whole sample of the questioned customs officers. The methodology used here is fully based on the probability theory with a partial use of the Analytic Hierarchy Process (AHP).

The AHP is a general theory of measurement. It determines relative classification scales using both discrete and continuous paired comparisons. It is widely used in multicriteria decision making and in conflict resolution. It is generally a nonlinear framework for carrying out both deductive and inductive investigations on observable experience feedback to estimate the expectation of new outcomes belonging to the same experience type.

The AHP was developed by T. L. Saaty in 1971- 1975 (Wharton School – University of Pennsylvania, Philadelphia), (T.L. Saaty, 1987). Besides, one may recommend other two papers (Pereyra -Rojas, M., 2017), and (L. Hammadi et al., 2016)) written in a didactic manner.

8 Individual Risk Indicators and Aggregation Algorithm

The individual risk indicators are aggregated in two steps.

Firstly, an independent and separate aggregation according to their technical nature to reduce them to 5 indicators: external-intelligence indicator (I_e), sniffer dog indicator (I_d), X-scan indicator (I_x), camera identification (I_c), and the inspection experience feedback indicator (I_o), opposite Figure 3.

Secondly, the final aggregation of the above 5 indicators into one Global Risk Indicator (I_G), carried on by the Risk Assessment Algorithm implemented in the BAG-INTEL Decision Support Tool. It is worth, at that stage, to note that the inspection experience feedback indicator (I_o) is a set of sub-indicators worked out based exclusively on the growing customs inspection experience feedback. It is the only dynamic indicator in the risk assessment tool. It allows the tool to learn more after each inspection act.

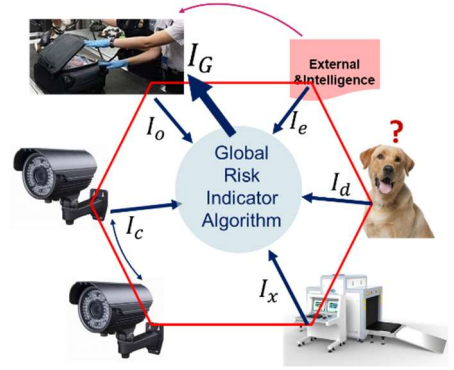


Figure 3:
Schematic presentation of risk indicators

8.1 Indicators Aggregation Algorithm

The Risk Assessment Algorithm flowchart is illustrated in the following, Table 4.

Table 4: Risk Assessment Algorithm Procedure

1. Risk Assessment Tool Activation on plan arrival
2. Retrieve External Data (I_e) and Target Risk Threshold (I_S)
3. Determine the relative weights ($w_{ij}^e, w_{ij}^d, w_{ij}^x, w_{ij}^c$) of all individual risk indicators ($I_{ij}^e, I_{ij}^d, I_{ij}^x, I_{ij}^c$)
4. Retrieve Dog and X-scan risk indicators (I_{ij}^d, I_{ij}^x)
5. Retrieve Camera Identification mismatching risk indicators (I_{c1})
6. Retrieve Camera Reidentification mismatching risk indicator (I_{c2}), if $I_{c2} = 1$, report "**Bag Lost**"
7. Determine Camera Identification and Reidentification Risk Indicator $I_c = 1 - w_c(1 - I_{c1}) \times (1 - I_{c2})$
8. Determine Weighted Risk indicators ($w_{ij}^e I_e, w_{ij}^d I_d, w_{ij}^x I_x, w_{ij}^c I_c$)
9. Determine the Global Risk Level (I_G) as:

$$I_G = [1 - (1 - w_{ij}^e I_e)(1 - w_{ij}^d I_d)(1 - w_{ij}^x I_x)]$$
10. Compare I_G and I_S , if $I_G \geq I_S$ recommend "Intrusive Inspection", if not "No recommendation"
11. Transmit comparison results and Cameras mismatching Risk Indicators to the "Customs Central" unit.
12. Check bags flow in, if that was the last bag GOTO #14 STEP, otherwise "Continue"
13. If any update occurred in the Ext Knowledge Risk Indicator, the Inspection Feedback weighting score, or the Threshold Risk Level then GOTO #2 otherwise to initialise all individual risk indicators inputs (I_d, I_x, I_c), GOTO #4
14. Sleep until next flight.

9 Calculations – Models & Preliminary Results

We recall that the Customs Inspection Feedback Experience database is still under construction. The preliminary results presented in the paper are not exhaustive, yet. Only less than half of the Customs Inspection feedback data (212350 inspections), section 6 (Annexe 1).

9.1 General Statistical Findings

The preliminary statistical assessment shows that the inspection decision making based on risk assessment and on behaviour assessment are almost of the same order, slightly higher in the case of behaviour assessment. That may be interpreted by the tendency of customs officers to classify random inspections under the category of “behaviour-based inspection”, if there is not an official “random inspection protocol” applied in their site, Figure 4(a).

Regarding risk-based inspection cases, Figure 4(b), 44% of the inspections are unsuccessful (no illegal substances are found) and 56% are either fully successful (35%) (the expected illegal substances are found) or partially successful (21%) (illegal substances are found but not the expected ones). It is almost the same data breakout in behaviour-based inspection, Figure 4(c), 43% are unsuccessful inspections, and 57% are either fully (30%) or partially (27%) successful.

It is worth noting that risk-based assessment boosts the full-successful inspections share by 6 points comparing to the partial-successful inspections. That is most likely due to its capacity to provide a better expectation of the illegal substances.

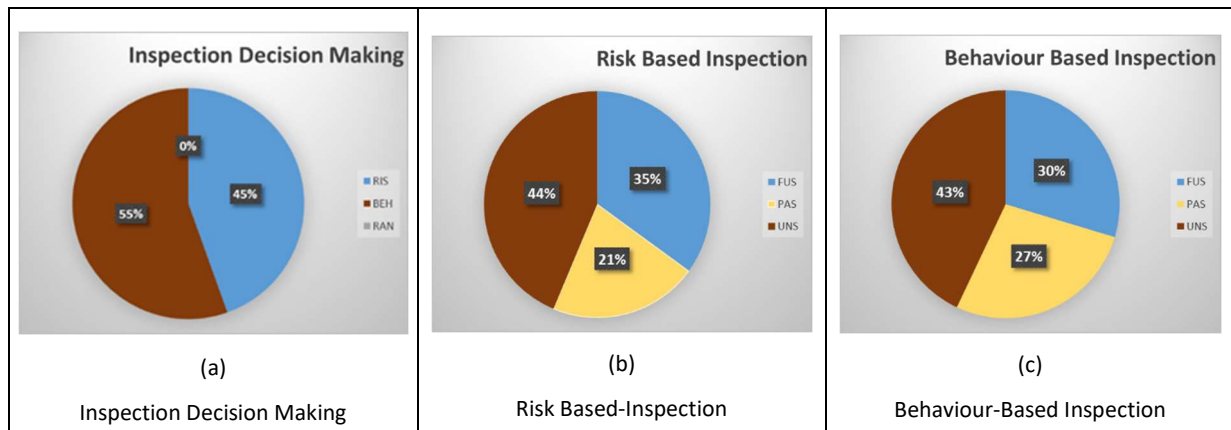


Figure 4: Preliminary statistical assessment of customs inspection experience feedback (212350 inspections)
(RIS: risk-based BEH: behaviour-based RAN: random-based)

Accordingly, we may make this statement “the state-of-the-art in risk-based inspection decision making proves that risk assessment enhances the expectation of illegal substances by 67%, $\left[\frac{35\%}{21\%} - 1 = 67\%\right]$. Then, any future progress due to the use of advanced risk-based inspection decision making should show a performance in the expectation of the illegal substances higher than 67%”.

But it is still astonishing that risk-based and behaviour-based inspections give similar unsuccessful inspection ratio. The authors hope that by the end of the full investigations this point could be explained.

9.2 Determination of the Weighting scores

Beside the general statistical remarks above, the second important output of the Customs Inspections Experience Feedback database is to assess the Individual Risk Indicators Weighting factors that will permit the determination of a Global Risk Indicator. The Customs Inspections Experience Feedback data contains two independent data categories.

The 1st category is the feedback of thousands of inspections scoring the trustworthiness level of customs in different data sources regarding separately each type of illegal substance, ex. table 4-1. Then, the relative scoring is done line by line (data source) in each column (illegal substance).

The 2nd category is the feedback of thousands of inspections scoring the trustworthiness level of customs in data concerning each type of illegal substance regarding separately different data sources, ex. table 4-22. Then, the relative scoring is done column by column (illegal substance) in each line (data source).

Tables 4-1 and 4-2, contain the average scores over 212350 inspections. These data are issued by subjective scoring done by customs inspectors. The numerical figures express subjective relative classification by column in Table 4-1 and by row in Table 4-2.

Table 4-1: Mean relative trustworthiness in Individual Risk Indicators (i) per illegal substance (j), (δ_{ij})

Individual Risk Indicators	Narcotics	Tabacos	Currency	Gold	Polymers
Intelligence & Knowledge (I_e)	4.7	6.1	5.2	5.9	6.7
Dog detection capability (I_d)	4.5	5.2	3.8	1.6	2.0
X-scanning (I_x)	2.9	7.7	5.5	5.9	6.7
Luggage photo identification (I_{c1})	1.0				
Luggage photo re-identification (I_{c2})	1.0				

Table 4-2: Mean relative trustworthiness in illegal substance (j) Individual Risk Indicators (i). (ε_{ij})

Individual Risk Indicators	Narcotics	Tabacos	Currency	Gold	Polymers
Intelligence & Knowledge (I_e)	4.8	5.5	5.0	5.3	5.9
Dog detection capability (I_d)	5.5	5.8	4.5	2.6	2.4
X-scanning (I_x)	3.7	7.9	5.3	6.3	6.9
Luggage photo identification (I_{c1})	1.0				
Luggage photo re-identification (I_{c2})	1.0				

9.3 Topology of the Individual Risk Indicators

The Individual Risk Indicators are real-time input data required by the risk assessment tool. Each of the indicators is issued from a different data source. Only, the Camera bag identification and re-identification scores are independent of the kind of the illegal substances. This difference in nature is considered during the numerical modelling and calculations.

However, all indicators have one common characteristic of interest. They all have probabilistic nature. As mentioned above, we are using simulated input data in the validation-in-principle of the risk assessment algorithm. In Table 5, it is shown a simulated input sample of the individual Risk indicators.

Table 5 : Simulated risk Indicators input data

Individual Risk Indicators	Narcotics	Tabacos	Currency	Gold	Polymers
Intelligence & Knowledge Databases (I_e)	60%	0%	40%	0%	0%
Dog detection capability (I_d)	45%	30%	15%	0%	0%
X-scanning (I_x)	55%	30%	15%	0%	0%
Camera bag identification (I_{c1})	20%				
Camera bag reidentification (I_{c2})	60%				

The simulated inputs in Table 5 are all probabilistic measures. The risk indicator (I_e) tells that there is a probability of 60% and of 40% that narcotics or currency notes, respectively, are transported on a given flight. The Camera identification (I_{c1}) success probability is about 80% ($I_{c1}=20\%$) and the reidentification success probability is 40% ($I_{c2}=60\%$).

9.4 Aggregation & Global Risk Determination Procedure

Using the simulated Risk input data (the individual risk indicators), the Global Risk Indicator is estimated to be about 78.6%. The Global Risk Indicators (I_G) tells that the probability of having a trafficking case in a bag is 78.6%. In case of the failure of the cameras identification and reidentification capacities, the risky bag will normally be intercepted with a probability of 30% thanks to behavioural and random inspections, Figure 4(c). Adding the cameras identification capacities, the interception expectation of the same illegal trafficking will jump from 30% to 55%. This demonstrates the critical contribution of the Camera identification and reidentification technologies in risk-based inspection decision making.

9.5 Relative Classification of the expected Illegal substances

Once the Global Risk Indicator (I_G) is determined, one's interest switches to the expected illegal substances and their expected classification.

The relative expected classification of the illegal substances is as such: narcotic with a score of 46.7%, Tabaco with a score of 28.1%, and currency with the score of 25.2%.

10 Conclusions

The EU Horizon project "BAG-INTEL" final target is to develop a Risk-based AI-tool to support customs intrusive inspection decision making relative to luggage control in airports. The Risk-based component of the AI-tool is powered by a risk assessment algorithm. The risk assessment algorithm mixes probabilistic statistics (deductive approaches) and Analytic Hierarchic Process (AHP) classification theory (inductive approach). The risk assessment algorithm does not exploit any AI-data processing technology.

The Algorithm and its implemented mathematical models are explained in a didactic manner to guarantee its successful implementation in the BAG-INTEL's tool to support customs intrusive risk-based decision-making processes.

The development of such an algorithm required building up a dedicated evolutive "Customs Inspection Experience Feedback Database" as the functioning of the algorithm requires some weighting factors issued from customs inspection experience feedback. The exploitation of such experience feedback requites equally the use of probabilistic-statistics and of inductive classification methods such as the AHP.

Some numerical experimental runs were carried out and other will still be run to identify the full extension of the informative outputs that can be expected from the algorithm and its mathematical models.

The preliminary results of the experimental runs gave a real insight into many aspects regarding the critical issues in a risk-based decision-making process in the field of customs intrusive inspection of luggage in airports.

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