

Article

The Impact of the Level of Training of Airport Security Control Operators on the Energy Consumption of the Baggage Control Process

Jacek Ryczyński *  and Artur Kierzkowski 

Department of Technical Systems Operation and Maintenance, Faculty of Mechanical Engineering,
Wrocław University of Science and Technology, Wybrzeże Wyspiańskiego 27, 50-370 Wrocław, Poland;
artur.kierzkowski@pwr.edu.pl

* Correspondence: jacek.ryczynski@pwr.edu.pl

Abstract: The article focuses on the study of the impact of the level of training of security control operators (SCOs) at airports on the energy consumption of the passenger baggage control process. With the constant growing emphasis on security at airports, the intensification of training processes for security personnel, especially those dealing with baggage control, has become very dynamic. An essential aspect in times of sustainable development is optimizing all kinds of processes (including training processes) to reduce energy consumption. The analysis of the demand for energy used to conduct this type of training and the impact of the operator's training level on the energy consumption of the control process are entirely ignored and have not been the subject of research by scientists so far. Therefore, this is a research gap that the authors are trying to fill in this article. The impact of safety system operator training levels on ensuring optimal energy efficiency was critically analyzed. The added value of the article is the authors' model assessing the influence of the level of training of the SCO on the energy consumption of the control process. The effects of the frequency, duration and level of operator training on energy consumption rates were investigated. The authors' activities aimed to identify the most energy-efficient approaches to training without compromising its quality and, thus, the safety of passengers. The article discusses potential strategies for minimizing energy use and draws conclusions that can help airport administrations and training providers adopt sustainable and energy-efficient training practices.



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Keywords: energy consumption; fuzzy logic; training; security control operator; SCO

1. Introduction

Over the past two decades, there has been a significant increase in primary energy consumption and CO₂ emissions globally by 50% [1]. Although there is no certainty about economic progress, forecasts indicate a significant escalation of global energy demand, with an expected increase of one-third from 2015 to 2040 [1,2]. This surge in energy consumption is expected to have a significant environmental impact in the coming years and could potentially lead to energy supply problems in some regions.

Typically, energy consumers are divided into three main segments: industrial, transport and other. Air transport is one of the most essential elements in the transport segment.

Airports are characterized by significant energy consumption, which is regulated by many factors. The nature of airport energy consumption is inherently unpredictable, non-linear and constantly changing. In academic circles, attention is often drawn to the energy consumption of terminal structures [1–4], even though they are only one (but a crucial) segment of the entire airport. As such, extensive exploration of the factors affecting airport energy efficiency has excellent potential for future research.

The primary energy consumption at airports can be divided into two parts: the aviation part and the land part. The aviation part includes mainly airport lighting and

radio navigation equipment. In turn, the airport terminal building dominates the land, partly due to its role as a central hub for passenger and cargo handling and the number of facilities necessary for its efficient operation. Therefore, innovative research methods to reduce energy consumption in such facilities are essential.

Electricity is the primary source for meeting the basic energy needs of airports and ensuring the safe handling of air traffic. Typically, electricity is sourced from the commercial grid through utilities. However, recent trends and the scientific literature [5–9] reveal the emergence of alternative energy sources such as combined heat and power plants (CHP) and renewable energy technologies. Nevertheless, given their different attributes and potential implications for air traffic safety, it is essential to establish rules that will harmonize airport operations with these alternative energy sources for the foreseeable future.

Nowadays, the issue of reducing energy consumption is the highest priority for airport administrators. The key strategies can be divided into the following groups: improvements to management systems and energy infrastructure, improvements to HVAC (heating, ventilation, air conditioning) and lighting systems, and the introduction of modern operational management systems to improve and optimize the energy efficiency of airports. In addition, using models and simulations to analyze airport energy consumption can play a crucial role in reducing consumption [3,4]. This requires the development of precise methodologies that cater to the unique environment of airports, with an emphasis that extends beyond the issue of terminal buildings. Moreover, while energy efficiency indicators (EEl)s provide energy managers with data on energy efficiency, they lack insight into the reasons for efficient or inefficient energy use. Therefore, there is a need to develop new analytical methods adapted to the specificity of airports, which will enable a comprehensive look at the issues of sustainable energy development in airports.

2. Literature Review

Optimization of the energy consumption management process to reduce its levels in air transport is widely discussed in the scientific literature. A comprehensive review of this issue was carried out in [2]. Taking into account the analyses contained in this work and supplementing them with the most recent research results, a clear research gap can be noticed in the research on the area of energy consumption in terminal passenger service, and in particular, in all kinds of aspects related to the security control of passenger luggage. It seems necessary to place appropriate emphasis on modeling and simulating energy consumption to ensure a high level of passenger safety while maintaining the principles of sustainable development in terms of energy consumption. It should be emphasized that the analyses included the entire airport and terminal buildings, with a dominant emphasis on HVAC systems [10–13]. Some studies have taken a more focused approach to specific topics. Ma et al. [8] studied the correlation between indoor airflow and indoor space to enhance indoor comfort. Parker et al. [9] aimed to reduce the carbon footprint by expanding the glass roof at a specific airport. Meanwhile, Gowresuunker et al. [14] evaluated the effectiveness of displacement ventilation in an airport terminal.

A group of articles also focuses on forecasting energy consumption in airport terminals. In this regard, Chen [15] used the objective Markov model, Huang et al. [16] used neural networks and Fan et al. [17] constructed a model based on probability density functions.

Mambo et al. [18] observed that the dynamic regulation of the internal environment by the flight schedule could bring improvements of up to 25%. Works [19–21] similarly recognized the possibility of dynamic thermal comfort and lighting management in various terminal spaces. In the literature, only a single paper refers to the energy consumption of terminal operations, and only two [3,4] directly correlate with the analysis of energy consumption by operating systems. In the work [4], a simulation model was developed that allows for the simultaneous analysis of the efficiency of the security checkpoint at the airport and energy consumption per serviced passenger. In the work [3], a simulation model was used to analyze the sensitivity of energy consumption by the baggage handling system at the airport to a change in the resource allocation strategy.

To sum up, a critical gap in the existing literature is the lack of research documenting the energy consumption of passenger service procedures, in particular baggage security checks. So far, attention has focused on other aspects. An extensive literature review on modeling passenger service processes is presented in [22]. The review found that the main factors were the efficiency of the process and the quality of passenger service. This approach has worked, and recent research confirms that these elements remain central to research efforts, as exemplified by the stochastic passenger boarding model developed to increase process efficiency [23].

In addition, uncertainty is considered when planning operations in airport terminals [24], and optimizing service processes remains the goal [25]. Optimal allocation of resources is often used to increase process efficiency [26,27].

Airports' energy management is a crucial matter from both economic and ecological perspectives. One of the primary challenges in this field is that the data about the total energy consumption of airports are classified as sensitive information, significantly restricting their public accessibility. Therefore, researchers and analysts must rely solely on estimated data to understand which airport processes consume the most energy.

A particularly scrutinized area is baggage control. This process is time-consuming and demands a substantial amount of energy, contributing a significant portion of the airport's overall energy balance. According to certain analyses cited in references [10,11,14], this process can account for 15% to even 20% of the annual energy consumption in terminal buildings, especially in large airports. Lighting and cooling have the largest share of energy consumption in airports. They account for 46% of total energy consumption. Hence, it is not a negligibly small value compared to the total consumption, indicating that undertaking analyses concerning efficient control process management is advisable.

Nevertheless, the developed solutions omit the aspects directly affecting energy consumption. This article tries to fill this gap. It aims to develop a model focusing on aspects that have so far been overlooked in research, i.e., the impact of the level of training of baggage screening operators at airports on the amount of energy consumption in the entire screening process.

3. The Process of Training Security Control Operators

The selection of appropriate personnel is crucial at passenger security checkpoints. SCOs play various roles, with the most important being the security screening of individuals and their carry-on luggage. Other duties include access control, monitoring the environment of the checkpoint, and inspecting gates and vehicles [21]. All these tasks require professional training. Before an SCO is assigned to a control position, they must undergo a cycle of preparatory training. The details and scope of each stage are presented in Figure 1. The training cycle concludes with certification, required by national or international regulatory bodies [28–35]. Obtaining a certificate and starting work does not mean the end of training. This process is ongoing and requires continuous improvement, especially in the use of emerging technical innovations and the introduction of modern technologies.

The implementation of advanced scanning systems, image analysis software, and other technological tools requires operators to keep up with changes and effectively use these tools in their work.

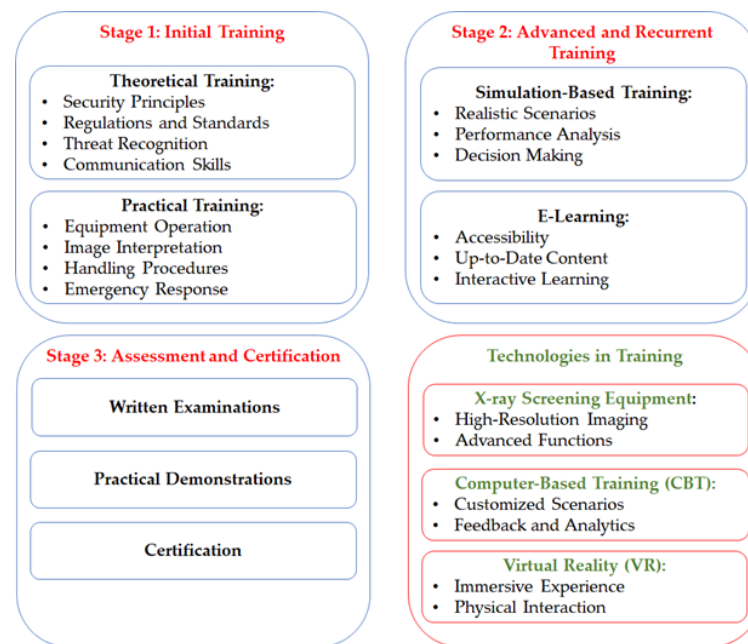


Figure 1. The stages of the training system for SCOs.

4. Methodology

The main research problem presented in this study is to create a model and an expert system that will allow us to assess the impact of the SCO training level at the airport on the energy consumption of the entire control process.

The proposed SCO training level assessment system is based on integrated knowledge of the critical skills of the operator. Preliminary research indicates the subjectivity of assessments and the difficulty in combining various indicators into one coherent assessment system, which inspired the authors to build such a system. To understand the complexity of the problem, the research concept is presented in Figure 2.

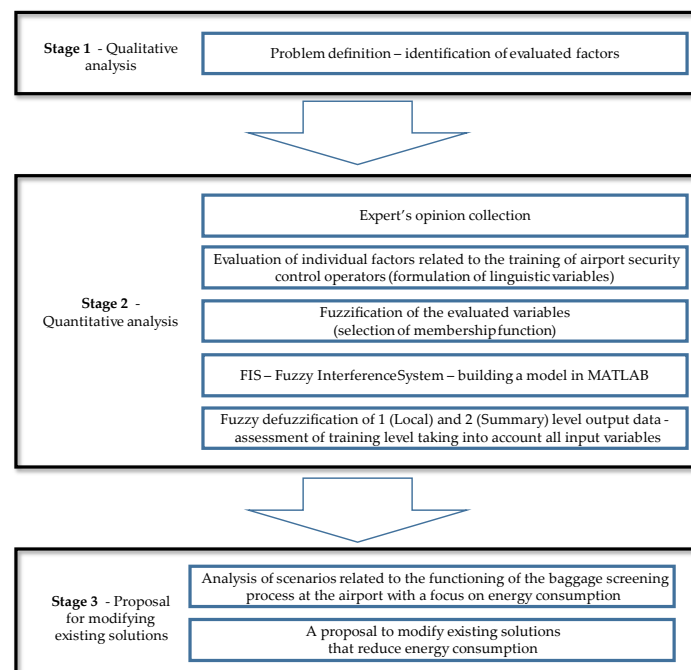


Figure 2. Research concept.

The above observations are the basis for adopting the concept in which the system for assessing the level of training and energy consumption of the inspection process will be based on an appropriate mathematical model that considers and integrates factors relevant to the assessment. In this situation, it is required to use methods that consider the imprecise and uncertain nature of the input variables [36–38]. In our study, we use the fuzzy set theory and its extension, the theory of fuzzy reasoning [39].

Fuzzy logic, being an extension of classical two-valued logic, is an indispensable tool in solving many engineering problems for various reasons. First and foremost, it allows for the modeling of uncertainty and imprecision, which often occur in real technical systems. It also enables the simulation of human reasoning, which naturally relies on fuzzy concepts rather than strict values. In the context of complex systems, fuzzy logic facilitates better management and control, which is crucial given the high level of complexity present in many systems (an example being the analyzed passenger service system at airports).

Moreover, it allows for the optimization of systems by considering various degrees of membership in fuzzy sets, which practically translates to the adaptability of systems, enabling them to learn and adapt to changing environmental conditions. Another advantage is the potential reduction in costs associated with designing and implementing new solutions in the field of system management or reducing the costs of using technical facilities. This, in turn, promotes the responsiveness of systems, which can react more effectively to changes in the environment, even when working with incomplete or imprecise data. It is also worth emphasizing the intuitiveness of designing systems using fuzzy logic, which allows for the use of linguistic variables that are closer to the human way of thinking. This compatibility with human reasoning means that fuzzy logic can be easily integrated with other computational intelligence techniques, creating hybrid intelligent systems.

Lastly, it cannot be overlooked that fuzzy logic has already found wide applications in practical technical systems, including industrial automation, robotics and risk modeling, which attests to its effectiveness in solving real technical problems.

Schematically, the fuzzy inference system is shown in Figure 3.

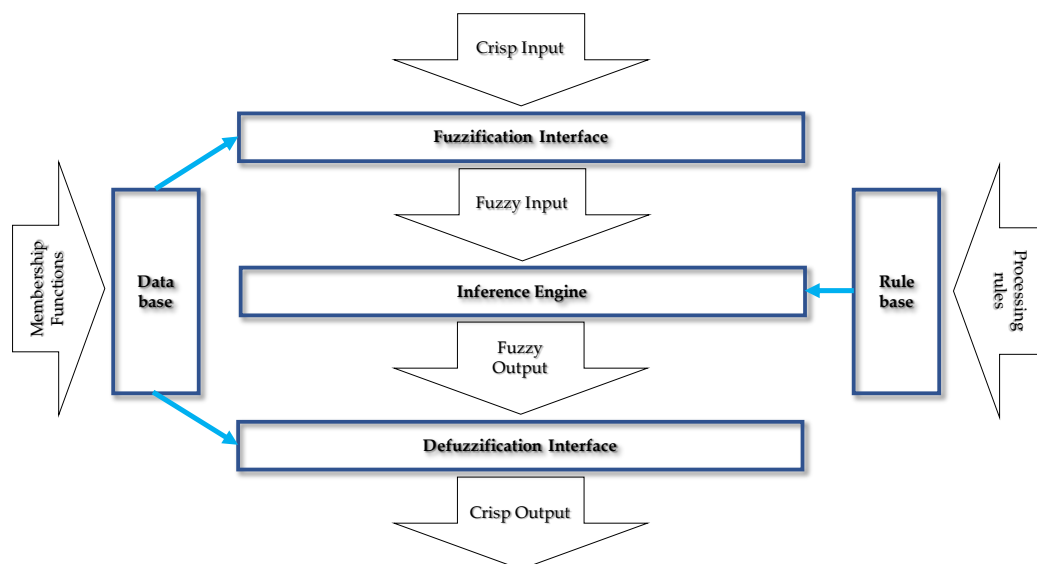


Figure 3. Fuzzy inference system.

The input of the fuzzy block is given the unfuzzy values from observations or measurements. In the blurring block, based on specific membership functions (MFs), they are associated with the values of linguistic variables, such as, for example, small, medium and large. The issue of determining the number of values of linguistic variables covering the entire space of consideration of a given variable, their form and the degree of overlapping of individual values must be determined each time when building a fuzzy reasoning system.

It is worth noting here that each unfuzzy input value may correspond to several linguistic variables with different degrees of membership. The fuzzy values are the input for the inference block. This block uses a fuzzy rule base, which, in the case of the methods used in this case, were created by experts: practitioners in the field of security control at the airport. Fuzzy inference rules are conditional sentences: IF premise THEN conclusion. Based on the fuzzy premises and all the rules met, the inference block determines the conclusion as a fuzzy linguistic variable. This conclusion is the input to the sharpening block, which, based on a defined MF, associates the fuzzy quantity with the original non-fuzzy quantity. It is the result of the fuzzy reasoning system. It is usually a number from some specific range.

Our solution was prepared in MATLAB version R2023a. The prepared fuzzy reasoning system uses local models of the Mamdani type. The fuzzy logic modules in MATLAB offer two analytical systems based on different approaches: Sugeno and Mamdani. The differences between these approaches are very significant. The Mamdani approach, which is more traditional, involves formulating fuzzy rules in a linguistic context, allowing for more intuitive system modeling. In contrast, the Sugeno approach focuses on formulating rules in a more mathematical context, facilitating precise modeling of functional relationships. In practice, Mamdani systems utilize membership functions described with words such as low, medium or high, while Sugeno systems operate on membership functions described by mathematical equations. This makes the Sugeno approach more oriented towards precision and mathematical analysis, while Mamdani focuses on linguistic interpretation. Moreover, Mamdani systems are generally easier to optimize and offer better computational performance compared to Sugeno systems. The Mamdani approach is often preferred due to its intuitiveness and ease of interpretation, making it more accessible to individuals without a deep mathematical background. It is important to note that both approaches have their place in designing fuzzy systems, and the choice between them depends on specific project requirements and the designer's personal preferences.

Mamdani-type systems allow the user to define input and output variables, determining their ranges and membership functions, which is a fundamental step in constructing a fuzzy system. Additionally, they can create various membership functions, including triangular, trapezoidal or Gaussian functions, enabling precise modeling of fuzzy relationships. A crucial element is also the ability to formulate fuzzy rules linguistically, facilitating the use of expert experience in the system design process. This tool also allows for the editing of existing rules, adapting them to changing project requirements. Users can utilize visualization options, including membership function plots and response surface charts, to better understand and analyze the system's operation. Within this tool, users also have the opportunity to simulate the functioning of the fuzzy system, observing its reactions to various inputs, which is essential for system verification and validation before implementation. A more advanced feature is the ability to optimize the built model, including adjusting membership functions and rules to achieve better results. After completing the design process, the fuzzy system can be exported to various formats or integrated with other systems in MATLAB, enhancing its utility in different application contexts. It is also worth noting the intuitive graphical user interface, which facilitates the design of fuzzy systems without the need to write code. Finally, Mamdani systems in MATLAB support various defuzzification methods, including the centroid, bisector, weighted average or maximum methods, allowing for controlled and user-expectation-aligned system output generation. Consequently, this tool represents a comprehensive solution for designing and analyzing fuzzy systems.

The Mamdani model performs its functions in the following stages:

1. Blurring: at this stage, the input values are transformed into fuzzy values using the MF. Each input variable has a specific MF that assigns to the input values the degree of membership of particular fuzzy sets.
2. Aggregation of premises (combining conditions): the conditions of individual rules are combined. If a given rule has several conditions, a fuzzy operator (e.g., T-norm) combines the degrees of membership of the conditions into one value.

3. Activation of rules: based on the aggregation value of the premises, the relevant rules are activated. Activation assigns a truth value (membership degree) to each rule. The truth value of a rule is equal to the aggregation value of the premises for the rule.
4. Activation of output sets: after activating the rules, the output sets are assigned activation values based on the conclusion of the rules. For each rule, the degree of membership for the conclusion is computed based on the rule's truth value. In practice, this means “trimming” the MF of the output sets to the truth values of the rules.
5. Aggregation of output sets: all activated output sets are combined into one output set using the aggregation operator (e.g., maximum, minimum or simultaneous minimum and maximum—MIN/MAX); details are in Figure 4.
6. Sharpening: transforming the fuzzy output set into one numerical value.

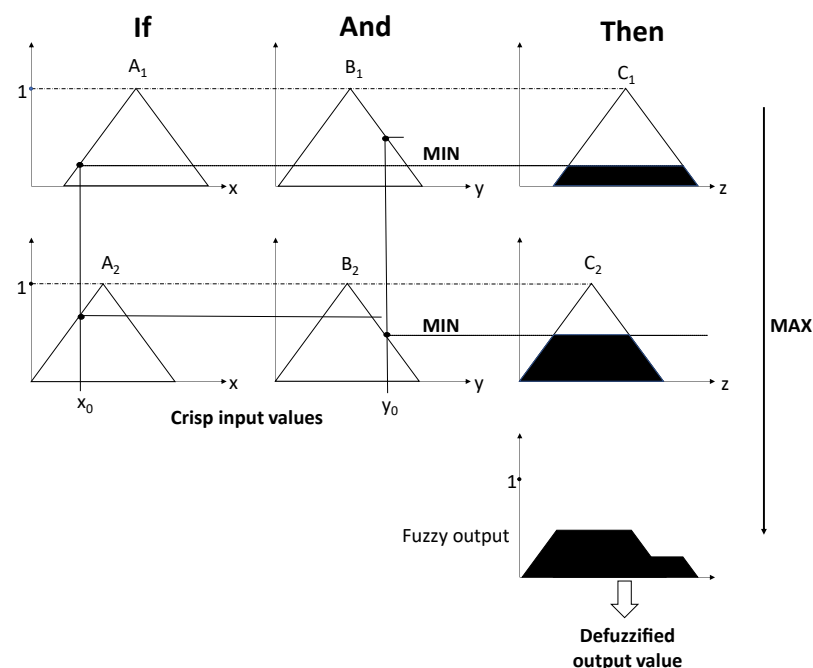


Figure 4. Functioning of FIS of Mamdani model using MIN/MAX operator for two activated output sets into one output (triangle MF).

The analysis of the problem of evaluating the level of training of SCOs drew attention to the need to include in the model and to have a thorough knowledge of the operators' skills in assessing X-ray images at security checkpoints regarding various categories of prohibited items. There are four categories: sharp objects, explosives, firearms and other prohibited items and substances. This observation was used to create a model. Thanks to this, it was possible to obtain an unambiguous assessment of the operator's level of training and to analyze partial results within four categories of hazardous objects.

A unique test stand was constructed to obtain the data necessary to build our fuzzy model. The core of the stand was the system that SCOs use daily. Such a station has not only been equipped with all the functionalities of a typical baggage control system at the control station. It was additionally equipped with the operator's eyeball tracking system, the so-called eye-tracker system. Additional equipment allowed us to obtain data to conduct analyses that are impossible to estimate in traditional systems, e.g., the time duration that the operator focuses their eyes on a dangerous object and many other parameters. The details will be discussed in Section 5. Figure 5 shows the appearance of the test stand equipped with the eye-tracker system.

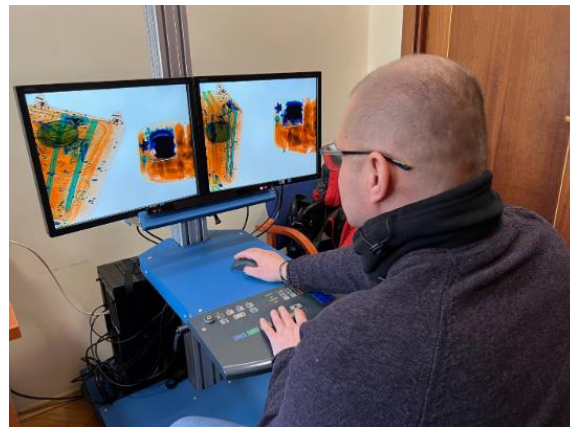
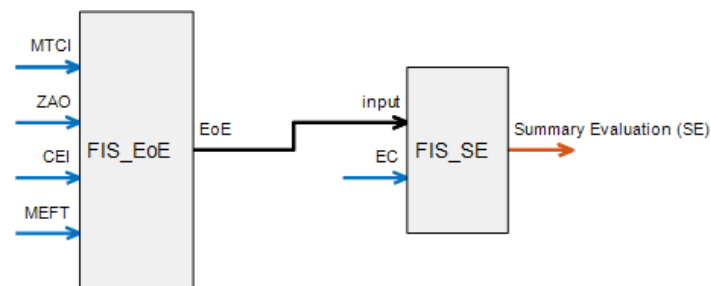


Figure 5. Test stand equipped with the eye-tracker system (an oblong black element mounted directly below the monitors for image observation).

5. The Model for Assessing the Impact of the SCO Training Level on the Energy Consumption of the Baggage Control Process

The model for assessing the impact of the SCO training level on the energy consumption of the control process was implemented as a fuzzy reasoning system. The analysis of the issues allowed us to propose a general structure for the model. Due to the nature of the problem, it has a hierarchical structure in which the outputs of the first-level fuzzy local models are inputs to the second-level fuzzy local models. Thanks to this, it was possible to obtain and analyze partial results, which are crucial for the conducted analyses. The model also includes the possibility of calibrating partial grades (and thus also the final grade) by taking into account the importance factor (issue importance) determined by experts. Systems of this type are based on the knowledge created on the basis of measurements and observations, as well as the knowledge of domain experts.

Details are shown in Figure 6.



Legend:

MTCl—Mean time to correctly indicate a dangerous item.
 ZAO—Zone analysis order (colors).
 CEI—Correct effectiveness indication.
 MEFT—Mean eye focus time on dangerous item.
 EoE—Evaluation of the effectiveness of hazard identification.
 EC—Energy consumption.
 SE—Summary Evaluation.

Figure 6. A fuzzy model for evaluating the impact of the SCO training level on the energy consumption of the baggage control process.

5.1. First-Level Local Models

Different mapping details on the analysis images characterize the dangerous element/object categories. Research shows that security control operators' training levels may vary for the four listed categories. However, the feature of the work of SCOs, consisting of looking for patterns in images of X-rayed baggage, consistent with typical images of

prohibited items, is common to all categories. Therefore, the constructed model has four first-level linguistic input variables. They include the following indicators:

1. Mean time to correctly indicate a dangerous item (MTCI): the average time expressed in seconds (s) necessary for the operator to indicate a dangerous object in the image, calculated based on the operator's eye movements tracked by the eye-tracker system;
2. Zone analysis order (colors) (ZAO): a dimensionless value, determined based on the operator's eye movements tracked by the eye-tracker system (details in the description of the variable);
3. Correct effectiveness indication (CEI): a variable describing the effectiveness of detection by the operator of objects, materials and substances considered prohibited; expressed as a percentage (%), calculated based on the quotient of correctly indicated dangerous objects among all those hidden in the images;
4. Mean eye focus time on dangerous item (MEFT): the average time expressed in seconds (s) that the operator focused on a dangerous object hidden in the image, calculated based on the operator's eye movements tracked by the eye-tracker system.

5.1.1. Mean Time to Correctly Indicate a Dangerous Item (MTCI)

The critical point affecting the overall throughput of an airport is the security check-point, where operators must quickly screen people and baggage effectively. The time it takes to handle a single passenger depends, among other things, on the level of training and experience of the security control operators. It is assumed that this time should not exceed 15 s. The research stage showed that, in the case of experienced operators, we rarely have a situation where the operator needs more than 11 s to analyze the image and thus indicate the prohibited element. Therefore, when describing a linguistic variable, the limiting value is 11 s (measured by tracking eye movements using the eye-tracker system). If the operator does not make a binding decision within this time, it means that they cannot assess the contents of the baggage, and proper intensive training is necessary at a certain level of difficulty. In real life, this factor is much more critical regarding potential consequences. Incorrectly conducted assessments may lead to a threat to the health or life of traveling passengers.

The linguistic variable “Mean time to correctly indicate a dangerous item” is represented by three values that describe the assessment of the level of training in the context of detecting prohibited items from this group: fast, medium and slow. Figure 7 shows the fuzzy sets describing the values for the linguistic variable “Mean time to correctly indicate a dangerous item”. These values are specified in seconds, allowing values to be read directly from the stand. Based on the research conducted on a control group of experienced SCOs, the following descriptions were adopted for MFs:

- Fast: time less than 7 s;
- Medium: time in the range of $7 \div 11$ s;
- Slow: time over 11 s.

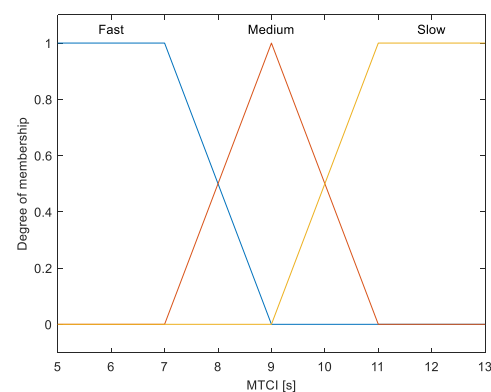


Figure 7. The form of the MF of the input linguistic variable “Mean time to correctly indicate a dangerous item”.

5.1.2. Zone Analysis Order (Colors) (ZAO)

The conducted research showed that, in the case of experienced operators, there is a specific pattern in the field of image analysis.

However, to fully understand the contents described in this section, it seems necessary to discuss how the image is obtained during the X-ray luggage screening with an RTG device. As a result of the screening, we obtain a layered image: the color represents the type of material, and the color intensity indicates its thickness. The thicker the object, the greater its intensity. In the basic view, the image color depends on the atomic number of the chemical elements constituting the object and is, accordingly:

1. Orange, for elements with an atomic number Z : $1 < Z < 10$;
2. Green, for elements with an atomic number Z : $11 < Z < 18$;
3. Blue, for elements with an atomic number Z : $Z > 19$.

The first group (orange color) includes objects such as light elements, hydrogen, carbon, nitrogen, oxygen and its chemical compounds, organic materials including many explosives, plastics like acrylic, paper, textiles, food items, wood and water. The second group (green color) includes medium-heavy objects: pure aluminum, sodium, chlorine, table salt, etc. The third group includes, among others, thin elements: metals, titanium, chrome, iron, nickel, copper, zinc, tin, silver, etc.

Depending on the thickness of the screened material, the color will be more or less intense, as the force with which the radiation is absorbed is visible in the form of correspondingly higher (thicker objects) or lower (thinner objects) color intensity. Objects that completely absorb radiation will appear black in the image. Similarly, when overlaying several layers of different objects, the color intensity increases.

The essential dangerous items detected in carry-on luggage include:

1. Liquids and other organic substances: the view depends on the material density, mainly visible in the primary image in green or orange;
2. Metal knives/gun parts: mainly visible in the image in the form of a blue shade of varying intensity;
3. Imitations of safe objects: no dominant color, the view depends on the material the object is made of.

Eye-tracking software can determine the share of the operator's gaze focused on individual colors in the image and, therefore, on dangerous objects. By analyzing how the operator's eye focus is positioned during image analysis, we can also determine the order in which individual colors are tracked, the mean time to correctly indicate a dangerous item and the mean eye focus time on a dangerous item.

Each operator first analyzes the blue areas, i.e., areas where weapons or sharp objects may be hidden. If they do not notice the shapes characteristic of prohibited items, they analyze the orange areas in search of explosive materials. At the very end, without indicating prohibited items, an analysis is carried out of the other colors in the image. The eye-tracker system enables accurate tracking of the eyeball movement and thus enables accurate analysis of zones and areas of observation. The linguistic variable "Zone analysis order" is represented by three values related to the observation time where the gaze is focused on the danger zones: short, medium and long. The analysis is carried out using the eye-tracker software, and the data are obtained directly from the stand. Figure 8 shows the MF describing the values for the linguistic variable "Zone analysis order". These values are expressed as a percentage. Based on the research conducted on a control group of experienced SCOs, the following descriptions were adopted for individual MFs:

- Short: less than 20% of observation time focused on hazardous areas;
- Medium: in the range of $21 \div 80\%$ of observation time focused on hazardous areas;
- Long: over 80% of observation time focused on hazardous areas.

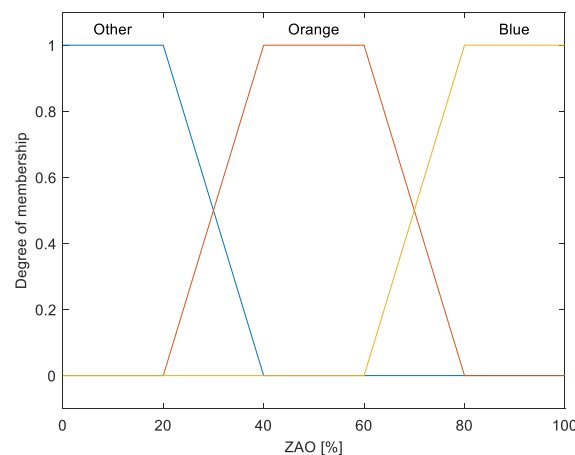


Figure 8. The form of the MF of the input linguistic variable “Zone analysis order”.

5.1.3. Correct Effectiveness Indication (CEI)

SCOs are expected to perform their task of detecting prohibited items and substances in baggage with a predetermined success rate. The minimum efficiency required from operators during their monthly examinations should not be lower than 75%. Of course, in the case of experienced operators, it is required that they achieve the best possible result, confirming the appropriate preparation for work at the security checkpoint, following the principle: the higher the detection rate, the greater the level of security guaranteed by the control point. In real-life conditions, where an employee experiences time pressure or a sense of great responsibility for passengers and is subject to constant control by supervisory authorities, achieving 100% efficiency in detecting prohibited items and substances in passengers’ luggage is almost impossible. Therefore, a threshold of 90% was adopted for the calculation, with the described linguistic variable as high efficiency. The linguistic variable “Correct effectiveness indication” is represented by three values that describe the assessment of the level of training in the context of detecting prohibited items from this group: unacceptable, medium and high. Figure 9 shows the MF describing the values for the linguistic variable “Correct indication effectiveness”. Based on research conducted on a group of experienced SCOs, the following descriptions were adopted for individual MFs:

- Unacceptable: score less than or equal to 75%;
- Medium: score in the range of 76 ÷ 95%;
- High: score over 95%.

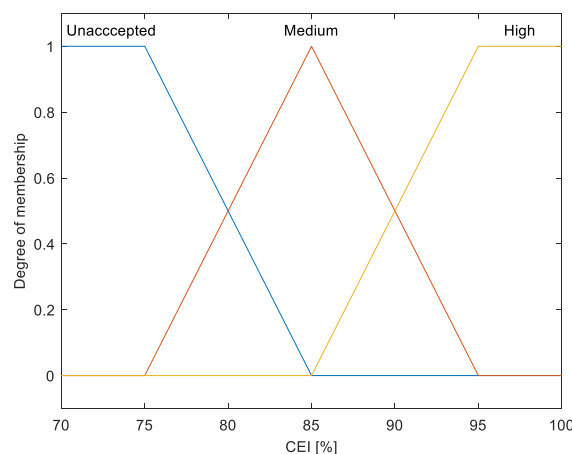


Figure 9. The form of the MF of the input linguistic variable “Correct effectiveness indication”.

5.1.4. Mean Eye Focus Time on Dangerous Item (MEFT)

The eye-tracker system allows you to add up the time the operator focuses his eyes on the prohibited item when analyzing the baggage image. The times read directly from the eye-tracker system described the linguistic variable “Mean eye focus time on dangerous item”. Research has shown that in the case of experienced operators, these times are similar (but consistently lower) than the average times for correctly indicating a dangerous object. This proves that an experienced operator detects a prohibited item quickly and spends the remaining time ensuring it is right before making a decision. This variable is represented by three values that describe the assessment of the level of training in the context of detecting prohibited items from this group: short, medium and long. Figure 10 shows the fuzzy sets’ MFs describing the values for the linguistic variable “Mean eye focus time on dangerous item”. These values are specified in seconds, allowing them to be read directly from the stand.

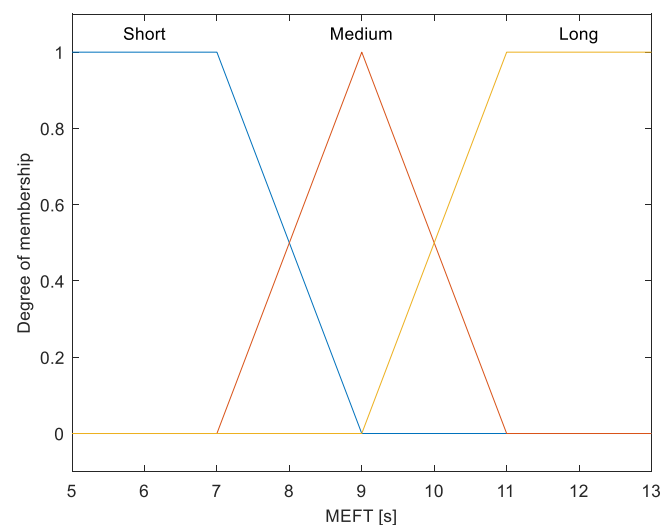


Figure 10. The form of the MF of the input linguistic variable “Mean eye focus time on dangerous item”.

Based on the research conducted on a control group of experienced SCOs, the following descriptions were adopted for individual MFs:

- Short: less than 7 s;
- Average: in the range of $7 \div 11$ s;
- Long: above 11 s.

5.1.5. The First-Level Local Output Variable: Evaluation of the Effectiveness of Hazard Identification

The first-level local output variable, which is also the second-level input variable, describes the assessment of the level of training in the context of detecting forbidden objects in images using four values: beginner, intermediate, advanced and experienced. Figure 11 shows the MF describing the values for the linguistic variables “Evaluation of the effectiveness of hazard identification”. These values are expressed as percentages on a scale from 0 to 100, which allows (after the defuzzification process) to compare them and perform mathematical operations directly. Based on the research conducted on a control group of experienced SCOs, the following descriptions were adopted for individual membership functions:

- Beginner: total score less than or equal to 50%;
- Intermediate: total score in the range of $51 \div 65$ %;
- Advanced: total score in the range of $66 \div 80$ %;
- Experienced: total score above 80%.

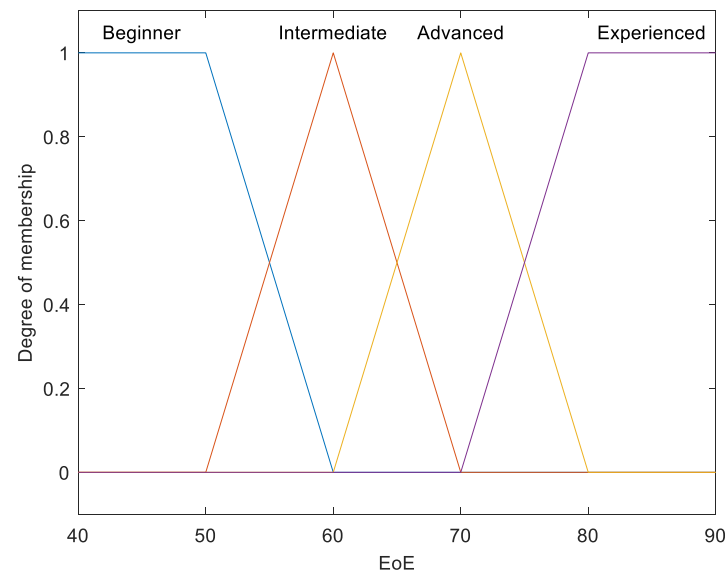


Figure 11. The form of the MF of the output(first-level)/input(second-level) linguistic variable “Evaluation of the effectiveness of hazard identification”.

5.2. Second-Level Local Models

The outputs of the first-level local models determine the training level of the SCO for each category related to image analysis to detect prohibited items. On this basis, in the second-level local model, the final, aggregated assessment of the SCO training level is made, considering the energy consumption of the entire process (variable Summary Evaluation—SE). We have two input variables at the second local level: Evaluation of hazard identification (EoE) effectiveness and Energy Consumption (EC). The first one is described in Section 5.1.

5.2.1. Energy Consumption (EC)

The “Energy Consumption” variable directly relates to the X-ray machine used to scan the baggage. In all our analyses, we considered an X-ray device with a smaller inspection tunnel size (100 × 100 cm and a standard penetration of 35 mm): scanner low power (LP). The advantage of this type of device is its small size and limited demand for energy consumption. The device consumes 0.262 kWh in the standby mode and 0.725 kWh in the operating mode (scanner). Due to the specificity of the magazine, it would be necessary to precisely describe the method of estimating the MF for the “Energy Consumption” variable. Research conducted by the team revealed that during one shift (lasting 8 h), an SCO participates in five sessions consisting of analyzing 50 images in each session. The operator analyzes 250 images during one workday, so the device is in permanent working mode. An experienced operator needs about 7 s to analyze a single image; an inexperienced operator may even need 15 s. The total working time of an experienced SCO is 1750 s for the task, and that of an inexperienced SCO is 3750 s. During this time, the former consumes 0.352 kWh (due to the very fast analysis of the device, it is constantly in scanner mode), and the latter consumes 0.497 kWh of energy (0.352 kWh from device operation and 0.145 kWh from the device being in standby during image analysis by an inexperienced operator). On this basis, limited values related to energy consumption during operation were adopted: low as up to 0.370 kWh; medium as 0.371–0.480 kWh; and high as above 0.480 kWh. The details are in Figure 12.

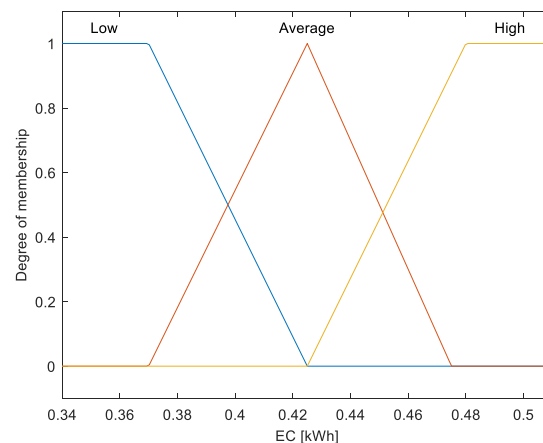


Figure 12. The form of the MF of the input linguistic variable “Energy consumption”.

5.2.2. Final Output Variable: Summary Evaluation (SE)

The final assessment of the level of SCO training is made using a five-point scale with three linguistic variables. To enable an unambiguous assessment, three levels of advancement were assumed, taking into account both purely technical aspects related to the security screening process and the impact of training on the level of energy consumption during the baggage screening process itself. Adopting a five-point rating scale with three linguistic variables greatly facilitates the construction of FIS engine rules (see Section 5.3) and limits their number, facilitating the analysis of results obtained during empirical or simulation tests. Based on research conducted on a control group of experienced SCOs, the following descriptions were adopted for individual MFs (details in Figure 13):

- Weak: sum of points below 1;
- Average: total score in the range of $1 \div 4$;
- Experienced: total score above 4.

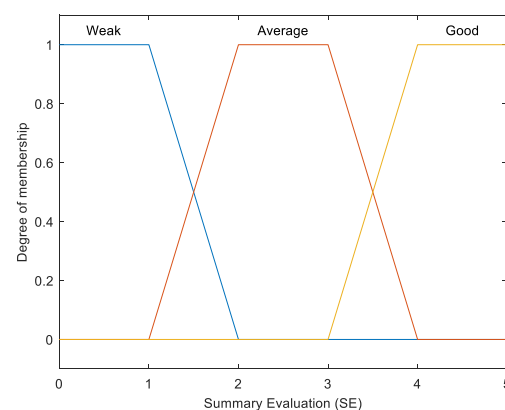


Figure 13. The form of the MF of the output linguistic variable “Summary Evaluation”.

5.3. Knowledge Base: FIS (Fuzzy Inference System) Rules

In the case of the presented model of assessing the SCO training level on the energy consumption of the control process, the knowledge base, which is a set of rules of the “engine” of the blurring system (FIS), is of a hybrid nature because it was created based on two different approaches. The first was acquiring knowledge from experts: specialists in creating and operating airport security control systems. The experts defined only part of the rules presenting the most important relationships between the input variables and the assessment of the level of training for a given category of prohibited items. In particular, experts indicated the importance of individual factors (input variables) in the

final assessment of the level of training. The remaining rules were generated automatically (and then verified for correctness) by the capabilities of the Fuzzy Logic Designer module of the MATLAB environment. The proposed method may involve machine learning algorithms such as unsupervised, supervised learning, optimization or genetic algorithms. Automatic rule generation can help fill in missing rules, optimize existing rules, or adapt the model to changing conditions.

A well-trained operator is an operator who quickly and effectively eliminates dangerous items from luggage, thus minimizing the energy consumption of devices supporting the screening process. In the case of creating the rules of the knowledge base, special attention was paid to the effectiveness of the correct indication of dangerous items. It is impossible to obtain the “experienced” level of training without sufficiently high efficiency. In the case of the presented model, 81 rules have been defined at the first level and 12 at the second level. An example fragment of the knowledge base is presented in Figure 14.

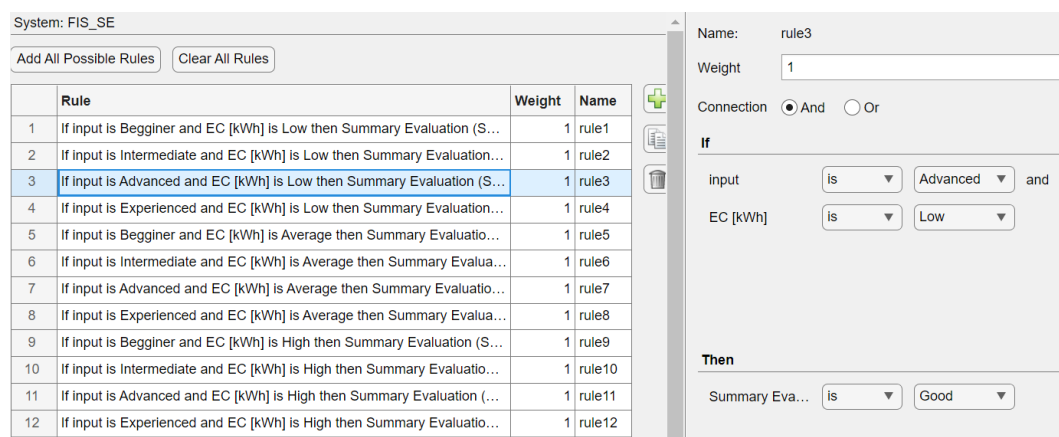


Figure 14. MATLAB window screenshot: example fragment of the knowledge base of SE.

6. Results

Experimental SCO tests were conducted to verify the built model’s correct functioning. In total, 18 operators were tested. The research was carried out in three groups:

- Operators with $0 \div 24$ months of experience in the position;
- Operators with $24 \div 90$ months of experience in the position;
- Operators with $90 \div 150$ months of experience in the position.

The tests were carried out on a built test stand using eye-tracking technology (see Section 4). As in real conditions, each operator was tested in threat recognition during five sessions with 50 images in each session. In total, each SCO analyzed 250 images. The images of baggage with (or without) threats that the operators analyzed were previously prepared by selecting groups of 50 photos from a database of almost 10,000 photos (the database was built as part of the project in cooperation with the airport). Each subsequent session was characterized by a greater difficulty scale (from the easiest to the most difficult). All operators were tested on the same group of images (displayed randomly within one session) to compare results. The test bench software allows you to read the total duration of an entire session (the total analysis time of 250 images). Based on this time, a script written in MATLAB calculated the energy consumption for a real X-ray station used in an airport for baggage screening. Details on how the time is calculated are described in Section 5.2, in the discussion of the Energy Consumption variable. The calculated variable was transferred automatically as input EC to the prepared fuzzy model. Based on the results of the tests, the total assessment of the operator’s training level was calculated. The results of the conducted research are presented in Tables 1–3.

Table 1. Results of experimental test SCOs.

No. of SCO	Experience in Position (Months)	The Value of the Parameter (Variable) Obtained in the Test					EC * (kWh)	SE
		MTCI (s)	ZAO (%)	CEI (%)	MEFT (s)	Summary Time of Sessions (s)		
Group 0 ÷ 24 months of experience in the position								
1	7	11.22	47	77	5.11	3123	0.45	1.95
2	9	10.56	48	79	7.23	2756	0.46	1.71
3	6	11.65	39	81	7.56	3154	0.45	1.89
4	7	10.82	48	77	8.33	3100	0.45	2.00
5	14	10.76	56	76	5.45	2974	0.45	1.99
6	9	12.03	43	78	7.41	2843	0.45	1.91
Group 24 ÷ 90 months of experience in the position								
7	48	9.11	65	79	8.56	2343	0.39	3.22
8	34	8.03	76	86	7.65	2245	0.38	3.47
9	32	9.31	67	96	5.44	2346	0.39	3.25
10	56	9.77	72	77	5.76	2567	0.41	2.87
11	48	8.44	66	88	6.43	2134	0.39	3.76
12	35	7.56	69	83	6.66	2056	0.37	4.03
Group 90 ÷ 150 months of experience in the position								
13	120	6.11	88	97	5.12	1536	0.31	4.24
14	96	7.07	74	92	5.83	1765	0.35	4.20
15	123	6.33	71	94	5.44	1654	0.33	4.17
16	134	5.45	89	92	4.08	1438	0.28	4.24
17	135	6.11	87	96	5.23	1546	0.31	4.24
18	94	6.34	66	94	5.06	1747	0.35	4.15

Legend: MTCI—mean time to correctly indicate a dangerous item; ZAO—zone analysis order (colors); CEI—correct effectiveness indication; MEFT—mean eye focus time on dangerous item; EoE—evaluation of the effectiveness of hazard identification; EC *—energy consumption of one SCO per day (during one shift: 8 h); SE—Summary Evaluation.

Table 2. Results of calculation of energy consumption of SCOs.

No. of SCO	Experience in Position (Months)	EC per Day (8 h) (kWh)	Mean EC per Day in Group (kWh)	Weekly EC per One SCO * (kWh)	Yearly EC per One SCO ** (kWh)
Group 0 ÷ 24 months of experience in the position					
1	7	0.45	0.45	2.25	135
2	9	0.46			
3	6	0.45			
4	7	0.45			
5	14	0.45			
6	9	0.45			
Group 24 ÷ 90 months of experience in the position					
7	48	0.39	0.39	1.95	117
8	34	0.38			
9	32	0.39			
10	56	0.41			
11	48	0.39			
12	35	0.37			
Group 90 ÷ 150 months of experience in the position					
13	120	0.31	0.32	1.60	96
14	96	0.35			
15	123	0.33			
16	134	0.29			
17	135	0.31			
18	94	0.35			

Legend: Weekly EC per one SCO *—5 working days a week (8 h each shift); yearly EC per one SCO **—300 working days a year.

Table 3. Scenario analysis results for different SCO group compositions depending on experience.

No. of Scenario	Group Experience in Position	No. of SCO	Yearly EC per SCO (kWh)	Summary Yearly EC per 1 Group of SCOs on 1 × RTG Scanner LP * (kWh)	Summary Yearly EC per 3 Groups of SCOs on 1 × RTG Scanner LP (kWh)	Summary Yearly EC per 3 Groups of SCOs on 3 × Lines of Control with RTG Scanner LP (kWh)	Summary Yearly EC for Big Airport with 6 Lines of Control (kWh)
1	0 ÷ 24 months	10	135	1350	4050	12,150	364,500
	24 ÷ 90 months	0	117				
	90 ÷ 150 months	0	96				
2	0 ÷ 24 months	0	135	1170	3510	10,530	315,900
	24 ÷ 90 months	10	117				
	90 ÷ 150 months	0	96				
3	0 ÷ 24 months	0	135	960	2880	8640	259,200
	24 ÷ 90 months	0	117				
	90 ÷ 150 months	10	96				
4	0 ÷ 24 months	5	135	1260	3780	11,340	340,200
	24 ÷ 90 months	5	117				
	90 ÷ 150 months	0	96				
5	0 ÷ 24 months	5	135	1155	3465	10,395	311,850
	24 ÷ 90 months	0	117				
	90 ÷ 150 months	5	96				
6	0 ÷ 24 months	0	135	1065	3195	9585	287,550
	24 ÷ 90 months	5	117				
	90 ÷ 150 months	5	96				

Legend: RTG scanner LP *—low-power X-ray scanner.

Based on the analysis presented in Table 3, it can be seen that the annual difference in energy consumption during the inspection of hand luggage using a low-power X-ray scanner between experienced and inexperienced SCO is 30%.

Experimental studies have shown that the area of passenger baggage security control requires the examination of factors that have been completely overlooked so far. One of these factors is the economic factor (represented by the energy costs of the entire baggage control process), which the authors included in this publication. A control group consisting of six SCOs, with two operators with experience from each group, which were subjected to the tests presented in the article, was used to calibrate the model (determining the boundary values during the estimation of MF values representing individual linguistic variables). Based on the studies of these operators at real workstations operated at the airport, all input variables of the model were calculated. The expansion of the research group and the obtained results (Table 1) indicate that the authors did not make mistakes while building the model. The research results show that, from an economic point of view, the effectiveness of detecting dangerous objects in passenger luggage cannot be the only criterion for assessing SCOs during the verification of their capabilities. The energy difference used to assess 250 images between the best of the operators (No. 16) and the weakest (No. 2) was over 0.17 kWh, to the disadvantage of the less experienced operator. The difference of 0.17 kWh is only seemingly small. It should be emphasized that this is the difference in energy consumption of a very low-power RTG scanner during baggage control, operated by operators with different levels of experience during one full working day (one shift lasts 8 h). During one shift, the security control team usually consists of 10 people (at medium-capacity airports). In the case of larger airports, this number can be higher. Moreover, one full day consists of three shifts, each with 10 operators. So, the seemingly small difference is multiplied by 30 (see Tables 2 and 3). Even in small local airports, there are at least three parallel security control lines, so this value increases even more. To show the impact of the level of training on the value of consumption, the authors analyzed six different scenarios (Table 3). In each scenario, the team of operators on one

shift lasting 8 h consisted of SCOs with a uniform (from the point of view of the obtained SE result) level of experience (scenarios 1, 2 and 3), and for comparison, a similar analysis was carried out for mixed teams (scenarios 4, 5 and 6). The authors emphasize once again that while preparing the evaluation tool, presented in the article, they took into account a very low-power RTG scanner. Scanners commonly used at airports have five times more power than the one used to build the tool. The tool presented in the article has a very universal character. To illustrate the scale of the problem to the reader, the authors presented the results of calculations for a large European airport equipped with control stations with high-power RTG scanners and six parallel security control lines for comparison in Table 3 (last column). In this case, the annual energy consumption difference in the entire process between teams of experienced and inexperienced operators amounted to over 105 000 kWh, thus showing savings reaching tens of thousands of euros.

At the same time, it was observed that with the increase in the operator's experience, the time of identification of dangerous objects (MTCI) in the luggage and the effectiveness of correct indication (CEI) were shortened. The same effect can be achieved by training the operator at appropriately prepared training stations devoid of the most energy-consuming elements, such as RTG scanners. Analyzing the data contained in Table 1, it can be seen that the overall training assessments (SE) of operators from the first group (experience at the position of less than 24 months) practically disqualify them from working as SCOs from an economic point of view (they formally meet the requirements regarding the CEI indicator value). This observation may be a hint for people managing the entire process of supervising baggage security control to train these least-experienced operators very intensively on simulators before they are allowed to work at real stations. Simulator training is stress-free and pressure-free, which additionally shapes habits and develops a certain automatism in the decisions made related to image analysis. The research showed that the most experienced operators almost automatically focused their gaze on dangerous objects for up to 82% (MFET/MTCI ratio: the average value for the entire group) of the time needed for correct indication, while beginner operators focused for only 60% of the time needed. The conclusions drawn allow people responsible for managing the entire security control process (supervising the work of operators) to create individual training strategies for each operator, which will significantly reduce the costs of the entire process.

7. Conclusions and Discussions

During the research, a large amount of experimental data was collected, which enabled the evaluation of selected parameters. These were then used to validate the assumptions made in the model.

The results obtained confirm the correctness of the assumptions adopted during the model construction stage. The analyses carried out indicate the possibility of effectively using the constructed model to make quick and highly effective diagnoses in terms of the level of SCO training (both in terms of general assessment and individual categories). Therefore, they provide the opportunity to appropriately plan the improvement training process, especially for operators showing deficiencies in individual areas.

The model presented in the article can be used to analyze the impact of various factors on the overall assessment of the level of operator training. The key conclusion from the conducted experimental research is that raising the level of SCO training greatly affects the level of electricity consumption, which has been proven in Section 6. To use its advantages even more effectively in the training process itself or at the stage of planning a training cycle, it is necessary to test a larger number of operators (especially those with the most experience) and possibly modify the model itself (e.g., in terms of the number of input variables). However, based on the experience gained so far, it is possible to propose the following scheme of work with the model and its implementation in the training process:

1. Preparation of input data: collecting information on individual factors affecting the level of SCO training, such as skills, experience, theoretical knowledge, etc. These data should be transformed into a form suitable for the inputs of fuzzy models.

2. Starting the simulation: based on the input data, a simulation is carried out, which allows the assessment of the impact of individual factors on the final assessment of the SCO training level.
3. Analysis of the results: analysis of the simulation results in terms of understanding how individual factors affect the assessment of SCO training. On this basis, training strategies can be developed to improve weaknesses and use strengths.
4. Experiments with different scenarios: it is possible to conduct various simulation experiments to study the influence of different combinations of factors on the final score. This can help determine the optimal training path for the SCO that will deliver the best results.
5. Verification and validation: after experimentation, the results can be verified and validated by comparing them with actual training results or other assessment methods.
6. Further improvement of the model: modifying the number of inputs to the model, MF, inference rules or hierarchical structure to obtain better results.

The quick and effective assessment of the SCO training level allows for the preparation of practical, personalized training strategies that will allow you to achieve the best results and thus contribute to improving passenger safety while guaranteeing optimization in electricity use and sustainable development.

In summary:

1. The research showed that differences in SCO experience significantly affect the energy consumption of the baggage control process. Operators with more experience consume less energy, which translates into significant savings, especially in large airports with multiple control lines.
2. Simulators, being less energy-consuming than actual RTG scanners, offer significant potential for training new operators, allowing them to develop skills in a stress-free and pressure-free environment, which additionally shapes habits and develops a certain automatism in the decisions made.
3. The built evaluation tool opens the way to developing individual training strategies for each operator, which can significantly reduce the costs of the entire process, with particular emphasis on training operators with less experience.
4. The authors of the study emphasize that economic analysis, represented by the energy costs of the entire baggage control process, is a significant factor that has been completely overlooked so far, suggesting that it should be included in the assessment of SCO operators' efficiency.
5. The tool presented in the article has a universal character and can be used to analyze various control systems, not only those based on low-power RTG scanners.

These conclusions suggest that both the training and professional experience of SCO operators are crucial for the efficiency and economy of the security control process, with the potential to significantly reduce operational costs and increase the efficiency of threat detection.

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