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Maximum likelihood estimation of probability for impact Resistance of safety guards

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The article examines the testing method described in Annex B of the ISO 14120 standard for assessing the impact resistance of machine guards. The typical testing practice involves firing a single shot from a ballistic cannon at the guard, with sensors measuring the projectile's velocity before and after impact. However, meeting the guidelines for this test presents challenges, including the difficulty of identifying and hitting the "weakest point" of the guard and ensuring the projectile strikes the surface in a perpendicular manner. The key findings, derived from a five-year collaboration between two research institutions, focus on analyzing uncertainties inherent in these standardized testing methods. Two statistical distributions, Logistic and Gaussian, are employed to process the data. The traditional approach of creating a histogram before calculating the cumulative distribution function (CDF) was found inadequate because it reduces the number of data points available for accurate curve fitting. To improve this process, the Probit method, already used in the AEP 2920-2016 standard, is introduced as a more effective regression technique for the Gaussian distribution. A comparison is made between results from different regressions, focusing on discrepancies in the tails of the curves, where the divergence between models becomes more significant.
The article also discusses methods for estimating the statistical dispersion of test results. Specific examples of trials carried out at the INAIL laboratories in Monte Porzio Catone are provided, showing the application of these methods in practice. These experiments were part of a joint research initiative between the University of Perugia and the Department of Technological Innovations and Safety of Plants, Products, and Anthropic Settlements (DIT). By presenting this research, the article seeks to address the practical limitations of standardized tests and suggests alternative methods to improve accuracy and reliability of machine guard impact resistance evaluations.

Keywords: Safety of machinery, Probit method, Guard impact resistance, Ballistic cannon, Penetration probability.

1. Introduction

The EU Machinery Directive (MD) 2006/42/EC (2006) is the primary reference for machine design. It specifies the principles that must be followed by manufacturers to meet the safety requirements for the design and construction of machinery. According to the MD, every possible risk must be eliminated or reduced through appropriate machine design. However, particularly in the mechanical field, most machine operations inherently involve hazards. When a hazard cannot be adequately reduced during the design phase, the best alternative is to implement protective equipment between the hazard source and the operator. For example, guards should be used to prevent contact with moving machine parts. Similarly, safeguards are commonly employed to protect individuals from potential impacts caused by objects that might be ejected from the machine, such as tools, workpieces, or parts of them. To comply with the directive, international standards such as ISO 14120 (ISO, 2015a) recommend the state-of-the-art procedure to ensure an adequate level of protection. In this procedure, the guard, or a section of it, is subjected to a high-velocity impact from a standardized projectile, and the resulting damage is assessed to determine the outcome. As outlined in the type B standard and further detailed in type C standards, such as ISO 23125 (ISO, 2015b), the test is considered successful if the damage is limited to elastic or plastic deformation without a fracture penetrating the entire thickness of the guard. This state of deformation, without a through-thickness crack (a continuous crack from one surface to the other), is referred to as the Impact Resistance (IR) of the material. However, if the deformation results in a continuous crack extending through both sides of the guard, the test is deemed a failure (see ISO 14120, Annex B, paragraph 2.4.1). In this study, a through-thickness crack will be classified as a failure (state 1), while a successful outcome will be indicated as state 0. This approach, which may differ from those used in other studies, such as the approach for protection of persons, will be explained in more detail later.

2. Probabilistic Exploration of Resistance of a Material, V_{bl} vs IR

Building on the understanding of impact resistance, one of the most efficient probabilistic analyses for studying high-velocity impacts was presented by Tahenti et al. (2017a). It is important to note that probabilistic methods are primarily used for determining the probability of full perforation of an armor, denoted as V_{bl} (50% of probability), which is different from the impact condition studied in this paper (called IR that will be explained in detail later). The well-known Recht & Ipson equation (Recht et al., 1963) is also able to predict residual energy of a projectile perforating a ductile material for any impact velocity higher than V_{bl}. Other testing techniques were implemented to find the full penetration state of a material; this refers to the condition in which a projectile perforates the material completely, with no residual velocity remaining after penetration. This state is not utilized in safety application for machine directive because it is considered an unsafe condition for the worker.

In this paper, the thorough-thickness crack condition, as explained in the introduction, is explored, highlighting how this phenomenon proves to be a trickier state to retrieve under a specified impact condition (Uhlmann et al., 2017).

However, some of the methods used for V_{bl} determination can be adapted to investigate IR_{50}, which is the 50% probability of obtaining a through-thickness crack. It represents the kinetic energy a guard can withstand from a projectile impact.

Generally, all strategies try to minimize the difference between predicted frequencies of fails and experimental data. Some authors have introduced Monte Carlo simulation methods (Davis et al., 2021) or Bootstraps Method to obtain the experimental distribution of the perforation probability, thereby reducing the need for costly experiments (Tahenti et al., 2017b).

Another effective technique for studying ballistic penetration is simulation using finite element analysis (FEA). This approach is a valid tool for investigating the interactions between projectiles and targets under high strain rates. Several studies have employed advanced FEA techniques to model the penetration of projectiles into various materials. For instance, in the work of Stecconi and Landi (2023), the authors used explicit dynamic analysis to simulate the impact of steel projectiles on polycarbonate plates, focusing on the plastic deformation and fracture mechanisms of the target material for safety guards. To replicate the penetration process and predict the perforation threshold accurately, the model must incorporate well-defined material properties and finely tuned erosion criteria.

Many similar studies demonstrate that a well-defined model, in terms of materials, damage models, and element erosion techniques, can effectively reproduce the results obtained in experimental tests of machinery guards, ensuring accurate predictions of impact resistance and failure in protective structures.

In addition to these studies, Uhlmann et al. (2022) introduced an alternative way for determining impact resistance (IR) through a statistical evaluation procedure. This approach facilitates a probabilistic characterization of IR using the cumulative distribution function (CDF) of a normal distribution. Rather than defining a fixed interval, this method expresses IR as the probability P of succeeding in the impact test. Uhlmann effectively employed this statistical technique across multiple series of impact tests conducted on polycarbonate (PC) sheets. However, due to a lack of evidence supporting the validity of the Gaussian hypothesis, another distribution was proposed for data regression. In 2023, the research groups led by Landi and Uhlmann jointly presented a different statistical approach (Uhlmann et al., 2023) that compared normal and logistic distributions. The CDF of the normal distribution was calculated using a histogram that classified 104 experimental tests into seven classes, revealing a good correlation between the curves. However, when the same procedure was applied to a smaller sample of tests using a four-class histogram, as presented by Landi et al. (2024), notable differences between the graphs emerged. Also, the previous work investigates the withstanding capacity in the VGZ interval described by Landi et al. (2022a).

Going back to V_{bl}, the ballistic penetration phenomenon is widely studied in military applications to ensure personal protection against threats. In this field, a large variety of materials can be used in protection construction; also, several ranges of projectile energies are possible due to the vast array of weapons and initial velocities. In this more diverse and complex scenario, Kneubuehl et al. (2003) presented an overview of the principles and test methods that can be used. Some guidelines emerge from the NATO STANAG which realizes standards such as the procedures for the evaluation and classification of personal armor AEP 2920 (2016). In the annex H.3 it introduces the procedure to statistically evaluate the probability of penetration, V50, of a protection, using the Probit method (Finney, 1952). The use of the likelihood function permits the determination of 95% confidence intervals for V_{bl}. Another body armor standard, from the U.S. department of justice NIJ 0101 (2008), describes rigorous testing of panels and specify to perform a regression to estimate the performances over a range of velocities. It ensures that different distribution and regression methods are possible suggesting however the logistic regression as adequate for the purpose. Annex D.2 of NIJ shows the function and the optimization method to estimate the parameters that define the S-shaped curve.

In this work, the authors apply Probit and Logit methods to perform data regression on experimental tests conducted on polycarbonate panels, comparing the results of the two regressions.

3. Testing Setup and Material Specification

3.1. *Gas cannon setup*

Due to space constraints, the experimental setup used at the INAIL laboratories in Monte Porzio will not be discussed here. A standardized 0.1 Kg projectile is employed for the tests. For details, see Landi et al. (2024).

3.2. *Material*

In the conducted tests, 4 mm thick PC panels measuring 300x300 mm were employed. The characteristics of the material are detailed in Table 1.

Table 1. Mechanical and physical characteristics of polycarbonate.

Characteristic (unit)	Value
Thickness (mm)	4
Tensile Strength (N/mm^2)	60
Elongation at tear (%)	110
Specific heat (J/g K)	1.3
Density (g/cm^3)	1.2
Modulus of elasticity (MPa)	2200

4. Description of the Test

The following paragraphs present and discuss the tests conducted to investigate the statistical behavior of IR. For each test, the impact velocity, residual velocity (where available), lost energy, and the result are indicated. In this context, 'failure' is defined as the formation of a through-thickness crack.

Figure 1 illustrates both sides of the guard that experienced failure, clearly showing a through-thickness crack. In borderline cases, water may be used to determine whether the crack extends continuously through the entire thickness of the material.

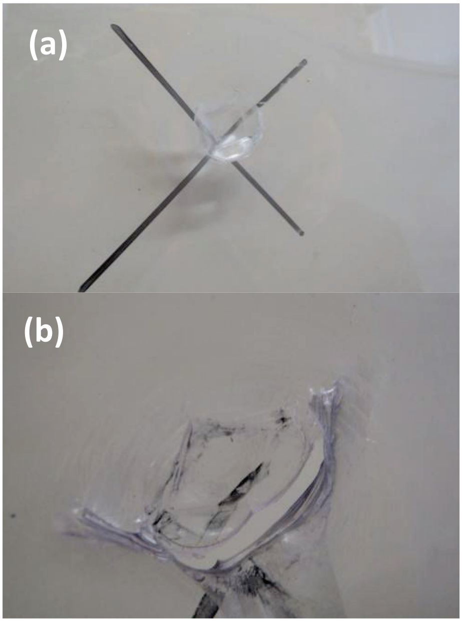

Fig. 1. Tested material. (a) Bulging and (b) Through-thickness crack.

The protective efficacy of a safeguard is commonly quantified by IR. In studies by Landi and Uhlmann, both Gaussian and Logistic distributions were found to be suitable for analyzing datasets where the continuous variable "Energy" serves as the input and the binary outcome (success or failure) as the output. Landi et al. (2024) performed a preprocessing step on the impact test results by converting the binary data into quantitative values. This was achieved by categorizing the results into energy ranges and calculating the probability of failure for each range. However, the article highlights that the limited number of tests constrained the creation of sufficient energy ranges, leading to a sparse dataset for curve fitting. Given the infeasibility of increasing the number of tests, an alternative regression method for constructing the cumulative distribution function (CDF) was considered.

4.1. *Probit method*

In statistics, a probit model is a type of regression where the dependent variable can take only two values. The purpose of the model is to estimate the probability that an observation with particular characteristics will fall into a specific one of the categories, see Eq. (1); moreover, classifying observations based on their predicted probabilities is a type of binary classification model. The perforation phenomenon is a stochastic event characterized by dispersion. This dispersion can be approached by a probability distribution which gives a perforation probability as a function of the impact energy. The theorem of the central tendency and experimental results have confirmed the choice of the normal law according to which the two parameters (μ and sd) are estimated by means of the PROBIT method. The presented approach is used in a similar purpose to study military protections of soldiers, and it is well presented in the standard AEP 2920.

$$P(u_i=1 \mid x_i) = \emptyset(Y_i) \tag{1}$$

Where:

- x_i : impact energy in the i-th test;
- u_i : result of the i-th test (1 for perforation, 0 otherwise);
- $\emptyset$: cumulative distribution function (CDF) of the standard normal distribution;
- Y : probit value.

Typically, the probit function is modelled as a two-parameter linear function. In this case, we use a single regressor, as shown in Eq. (2):

$$Y_i = \beta_0 + \beta_1 x_i \tag{2}$$

In linear regression, the sum of squared deviations is used as a measure of goodness-of-fit, with the best fit achieved when this function is minimized. However, with a cumulative function, error losses are not evenly distributed, which requires a different approach. Therefore, the goodness-of-fit for the Probit method uses the log-likelihood loss function, see Eq. (3):

$$LL = \prod_{i}^{n} \left[u_i P_{u_i=1} + (1-u_i) P_{u_i=0} \right] \tag{3}$$

Note that $P_{u_i=0}$, Eq. (3), is the complementary probability to $P_{u_i=1}$. The parameters $[\beta_0, \beta_1]$ are estimated by maximizing the log-likelihood function. The best fit is found by setting the partial derivatives of the log-likelihood function to zero, as shown in Eq. (4):

$$\begin{cases} \dfrac{\partial \mathrm{LL}}{\partial \beta_0} = 0 \\ \dfrac{\partial \mathrm{LL}}{\partial \beta_1} = 0 \end{cases} \tag{4}$$

Since LL function is nonlinear in β_0 and β_1, determining their optimum values will require numerical methods. It can be shown that this log-likelihood function is globally concave, and therefore standard numerical algorithms for optimization will converge rapidly to the unique maximum. The maximization procedure can be accomplished by solving the above two equations; the algorithm that is used take the name of maximum likelihood estimation (MLE). The relationship between the optimal parameters, the mean and the standard deviation of the Gaussian is exhibit below in Eq. (5):

$$\begin{cases} \mu = -\dfrac{\beta_0}{\beta_1} \\ sd = \dfrac{1}{\beta_1} \end{cases} \tag{5}$$

The impact test data are used as supporting points to fit a Gaussian distribution. The fitting process was conducted using MATLAB R2018a (The MathWorks, Inc., 2018) via the 'glmfit' command for the data presented in Table 2. The resulting fit is shown in Figure 2, and the corresponding results are presented in Table 3.

4.2. *Logit method*

An alternative representation of the probability of observing failure in an impact test is provided by the logistic distribution (Montgomery and Runger, 2014). The logistic function is a monotonically increasing, S-shaped curve, and the optimal fit is achieved by maximizing the log-likelihood estimator, which allows for determining the best-fit parameter values (Hosmer and Lemeshow, 2000). Similar to the Probit method, the Logit method is employed to statistically describe the impact phenomenon.

The NIJ 0101 standard illustrates the application of the logistic distribution in characterizing the resistance of body armor subjected to impact. The procedure outlined in this standard mirrors that used in the Probit method; however, in the case of the Logit method, the sigmoid function S is utilized, as shown in Eq. (6):

$$S = \frac{1}{1+e^{-t}} \tag{6}$$

where t is defined as a linear function of the parameters, given by Eq. (7):

$$t = \beta_0 + \beta_1 x_i \tag{7}$$

Figure 2 illustrates the comparison between the two regression methods in relation to the experimental points and the failure percentages for each point. It is important to note that the extremes of the graph do not correspond to the length of the VGZ interval; in fact, the domains of the functions have been enlarged to ensure visibility of the curves' tails. The two regression methods appear to be largely interchangeable, yielding similar values primarily around the IR_{50} threshold, although some minor differences are observed at the tails of the regressions. Summary data for the regressions are presented below.

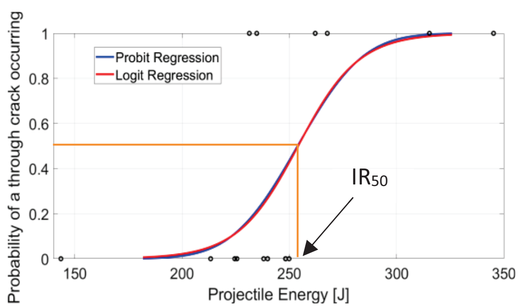

Fig. 2. Comparison of the Probit and Logit regressions.

Table 2. Test data (0 bulging, 1 through crack).

Test number	Energy [J] (Test result)	Test number	Energy [J] (Test result)
1	143.53 (0)	9	239.88 (0)
2	213.30 (0)	10	248.17 (0)
3	224.53 (0)	11	248.32 (0)
4	225.57 (0)	12	249.88 (0)

Table 2 (Continued)

5	231.34 (1)	13	262.04 (1)
6	234.79 (1)	14	267.67 (1)
7	238.01 (0)	15	315.24 (1)
8	239.81 (0)	16	345.14 (1)

Table 3. Best fit regression data.

Fitting Parameter	Probit Regression	Logit Regression
Mean	253.8 [J]	254.1 [J]
Std	24.0 [J]	14.1 [J]
LL	-6.943	-6.941

Note that if a failure were indicated as 0, the curves in Figure 2 would be the mirror image with respect to the vertical axis passing through IR_{50}.

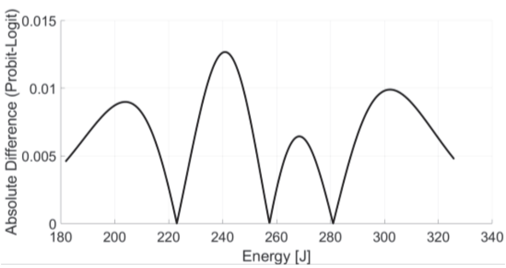

Fig. 3. Absolute difference between the Probit and Logit curves.

Figure 3 illustrates the observed differences between the regression methods. The largest discrepancies are found around the tails, with a maximum difference of approximately 1.3%. Overall, both methods effectively describe the withstanding capacity within the VGZ interval of the safeguard, showing only minimal differences.

5. Validation Method

Validation of the proposed regression models is essential to minimize potential errors and ensure reliable predictions. Since both regressions are nonlinear, the coefficient of determination (R^2) is not a suitable metric for assessing the model's goodness of fit (GOF). For small datasets, McFadden's pseudo-R^2 (McFadden, 1977) is a more appropriate measure. As highlighted by Uhlmann et al. (2024), pseudo-R^2 values in the range of $0.2 < R^2 < 0.4$ generally indicate a good model fit for nonlinear regressions such as logistic models. In this study, the obtained pseudo-R^2 value of $R^2 = 0.34$ suggests that the model fits the data well. However, while the pseudo-R^2 provides a statistical measure of the model's alignment with experimental data, it does not guarantee the accuracy of predictions, particularly at the tails of the distribution, as emphasized by Uhlmann et al. (2024). Indeed, the validation approach proposed by Uhlmann encountered discrepancies when evaluating the lower energy side of the curve during the validation phase. To better characterize the regression tail, a novel validation method was developed assessing the physical plausibility of predictions in the low-probability failure range, specifically within $0.01< p <0.1$. This approach is particularly relevant for safety applications and accurate determination of failure thresholds is critical.

In the first phase, an initial set of two impact tests is conducted at a projectile energy level corresponding to a predefined failure probability p. The binomial distribution is employed to calculate the likelihood of observing a through crack (0, 1, or 2 failures) from these trials. Table 4 summarizes these probabilities for $p = 0.0266$.

Table 4. Probability of observing 0 to 2 failures for n=2 tests at the same energy level, with p=0.0266, based on the binomial distribution.

Number of failures	Value
P (0)	94.93%
P (1)	5.00%
P (2)	0.07%

According to this validation framework, a null hypothesis (H0) is defined, asserting that the regression model is valid, while the alternative hypothesis (H1) postulates the model's invalidity determine that the whole tests shall be repeated to validate the regression's tails.

For instance, if 5% threshold for H0 is agreed, the decision-making process for the first phase is as follows:

- Case 1: no failures (P(0)) are observed. H0 is accepted, and the model is deemed valid.
- Case 2: a single failure (P(1)) is observed. This outcome neither strongly supports H0 nor H1 and requires further investigation.

- Case 3: two failures (P(2)) occur. H0 is rejected, and H1 is accepted, indicating that the regression model is invalid.

To resolve the ambiguity in Case 2, a second test phase is initiated, consisting of two additional impact tests. At this stage, the occurrence of one prior failure makes P(0) infeasible. Table 5 provides the updated probabilities of observing 1, 2, or more failures across all four tests, while the decision rules for the second phase, using the same 5% probability criteria, is as follows:

- Case 4: no more than one failure is observed in the four tests. H0 is accepted, and the model is deemed valid.
- Case 5: observing two or more failures across four tests would strongly suggest model invalidity, leading to the rejection of H0.

Table 5. Probability of observing 0 to 4 failures for n=4 tests at the same energy level, with p=0.0266, based on the binomial distribution.

Number of failures	Value
P (0)	90.12%
P (1)	9.50%
P (2)	0.38%
P (3)	0.0066%
P (4)	<0.0001%

This two-phase method is specifically designed to balance statistical rigor and safety considerations. The first phase focuses on minimizing the risk of a Type I error (incorrect rejection of H0), while the second phase addresses the risk of a Type II error (failure to reject H0 when it is invalid). By extending the validation to four tests in the second phase, the method increases its statistical power, thereby enhancing the reliability of conclusions regarding the regression model's validity. Additionally, this iterative approach improves the robustness of the decision-making process by incorporating further experimental data.

6. Validation Tests

The binomial validation method described earlier was applied to the polycarbonate (PC) panels under investigation, using the Gaussian regression model as the reference framework. This approach aimed to evaluate the model's ability to predict the tails of IR probability distribution. The threshold value for the Gaussian regression results to a value of p = 0.0266. The corresponding energy value is 190 J (v_d = 61.7 m/s). Because of the uncertainties of the tests the error on the evaluation of impact velocity is around ±2 m/s. In order to assure an impact velocity greater than v_d, the validation tests are performed with a velocity of about $v_{val} = v_d + 5\ m/s$.
Two shots were executed with measured impact velocities of 66.2 m/s and 66.3 m/s. Both tests concluded successfully, with no through-crack formation observed in the panels.

According to the validation procedure, these results suggest that the Gaussian regression model provides an accurate description of the IR behavior of the PC panels within the tested probability range. To further investigate the robustness and reliability of the novel validation method, the same validation tests were repeated under identical conditions (impact velocity 65.7 - 66.5 m/s). Consistently, no through-cracks were observed in the repeated tests, reinforcing the initial findings and offering additional confidence in the Gaussian regression model as a predictor of panel safety performance.

7. Conclusion

In this paper, the authors present a procedure for statistically evaluating the probability of failure of machine guards by analyzing the statistical distribution within the VGZ interval, based on the ballistic limit. Two methods already used for testing defense armor and general military equipment have been adapted for this purpose. According to the log-likelihood estimator, both models demonstrate good fitting performance and yield comparable results. However, small differences between the two curves become more apparent towards the tails of the distributions.

As future standards are expected to establish reliable maximum impact energy thresholds for specific safeguards, achieving low failure rates (with 1%-10% being reasonable targets) will be essential. Therefore, the validation method proposed in this paper offers a reliable approach for verifying the acceptance of the implemented models. This method ensures, with a certain probability, that the desired energy resistance threshold is equal to or lower than the values predicted by the Probit or Logit models.

Finally, to determine which distribution better reflects actual behavior, a larger number of tests should be conducted. Nonetheless, the authors believe that this combined approach, using Probit or Logit regression alongside test validation, will contribute to the creation of a safer workplace for operators by enhancing protective measures.

References

European Parliament and of the Council. (2006). *Machinery Directive 2006/42/EC. Official Journal of the European Union*, L157/24, 9 June 2006.

ISO. (2015a). *Safety of Machinery – Guards – General Requirements for the Design and Construction of Fixed and Movable Guards (ISO 14120:2015)*. International Organization for Standardization, Geneva, Switzerland.

ISO. (2015b). *Machine Tools – Safety – Turning Machines – Part 1: Safety Requirements (ISO 23125:2015)*. International Organization for Standardization, Geneva, Switzerland.

Tahenti, B., Coghe, F., Nasri, R., and Pirlot, M. (2017a). Armors ballistic resistance simulation using stochastic process modeling. *International Journal of Impact Engineering*, 102, 140–146.

Rech, R. F., and Ipson, T. W. (1963). Ballistic perforation dynamics. *Journal of Applied Mechanics*, 30(3), 384–387. The American Society of Mechanical Engineers (ASME). DOI: 10.1115/1.3636566.

Uhlmann, E., Meister, F., and Mödden, H. (2017). Probabilities in Safety of Machinery – Hidden Random Effects for the Dimensioning of Fixed and Moveable Guards. 15th Int. Probabilistic Workshop, Dresden.

Davis, B. G., J. Thompson, W. Morningstar, E. McCool, V. Peri, and F. T. Davidson. 2021. "Risk Evaluation of Ballistic Penetration by Small Caliber Ammunition of Live-Fire Shoot House Facilities with Comparison to Numerical and Experimental Results." *Journal of Defense Modeling and Simulation: Applications, Methodology, Technology* 12 (4). https://doi.org/10.1177/2041419620988553.

Tahenti, B., Coghe, F., and Nasri, R. (2017b). Accuracy analysis of the Brownian motion approach for the ballistic resistance estimation: Comparison of numerical and experimental distributions. *22nd International Congress on Modelling and Simulation*, Hobart, Tasmania, Australia, 3–8 December 2017.

Stecconi, A., and Landi, L. (2023). FE analysis for impact tests on polycarbonate safety guards: Comparison with experimental data and statistical dispersion of ballistic limit. *Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering*, 9(3), 1–13.

Uhlmann, E., Polte, M., Bergström, N., and Mödden, H. (2022). Analysis of the effect of cutting fluids on the impact resistance of polycarbonate sheets by means of a hypothesis test. *Proceedings of the 32nd European Safety and Reliability Conference (ESREL 2022)*, Research Publishing, Singapore, 2,358–2,365.

Uhlmann, E., Polte, M., Bergström, N., Burattini, L., and Landi, L. (2023). Comparison of a normal and logistic probability distribution for the determination of the impact resistance of polycarbonate vision panels. *Proceedings of the 33rd European Safety and Reliability Conference (ESREL 2023)*, 3–7 September 2023, University of Southampton, United Kingdom.

Landi, L., Burattini, L., Paolucci, F., Del Prete, E., Ratti, C., and Pera, F. (2024). Determination of impact resistance of aluminum panels for machine guards using regressions of dataset. *Proceedings of the 34th European Safety and Reliability Conference (ESREL 2024)*. ISBN 978-83-68136-17-3 (printed), ISBN 978-83-68136-04-3 (electronic).

Landi, L., Uhlmann, E., Hörl, R., Thom, S., Gigliotti, G., and Stecconi, A. (2022a). Evaluation of testing uncertainties for the impact resistance of machine guards. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering*, 8, 021001-1–021001-7.

Kneubuehl, B. P. (2003). *Ballistic Protection*. Swiss Defense Procurement Agency, Thun.

NATO. (2016). *AEP-2920: Procedures for the Evaluation and Classification of Personal Armour: Bullet and Fragmentation Threats (Edition A, Version 2)*. NATO Standardization Office (NSO).

Finney, D. J. (1952). *Probit Analysis: A Statistical Treatment of the Sigmoid Response Curve* (2nd ed.). Cambridge University Press. (Original work published 1947).

National Institute of Justice. (2008). *Ballistic Resistance of Body Armor: NIJ Standard-0101.06*. U.S. Department of Justice. Available at: https://www.ojp.gov/pdffiles1/nij/223054.pdf.

The MathWorks, Inc. (2018). *MATLAB R2018a*. Natick, Massachusetts, United States.

Montgomery, D. C., and Runger, G. C. (2014). *Applied Statistics and Probability for Engineers* (6th ed.). John Wiley & Sons.

Hosmer, D. W., and Lemeshow, S. (2000). *Applied Logistic Regression* (2nd ed.). John Wiley & Sons.

Uhlmann, E., Bergström, N., Demidova, C., and Meurer, F. (2024). Logistic Regression In Practice: Determining Impact Resistance Of Polycarbonate Vision Panels With Limited Data Set. *Proceedings of the 34th European Safety and Reliability Conference (ESREL 2024)*. ISBN 978-83-68136-15-9 (printed), ISBN 978-83-68136-02-9 (electronic).