The 11th International Congress
Motor Vehicles & Motors 2026
Kragujevac, Serbia
October 8th-9th, 2026

Motor Vehicles & Motors

MVM2026-032
https://doi.org/10.24874/CMVM2026.032
Original scientific paper

Zoran Papić[1]
Nenad Saulić[2]
Milja Simeunović[3]

PREDICTION OF EES VALUES IN VEHICLE IMPACTS USING AI

ABSTRACT: The energy equivalent speed (EES) is an important parameter for determining vehicle impact speed. It represents the portion of a vehicle's speed dissipated through deformation work during a collision. While this value can be calculated, determining it requires data on the depth of vehicle deformation across the entire width of the damaged area. This information is most often documented through photographs. Consequently, in traffic accident analysis, the EES value is usually estimated subjectively by experts through a comparison of photographs taken during or after the accident with reference images from electronic EES catalogues. The application of information technology (IT) in traffic accident analysis has enabled the use of artificial intelligence (AI) to predict EES values based on the correspondence between the observed damage to the vehicle under analysis and the damage documented for similar vehicles in EES catalogues. This paper presents an analysis of the capabilities and reliability of AI-based tools for estimating EES values for vehicles using tools integrated into the PC-Crash software environment based on convolutional neural networks (CNNs).

KEYWORDS: Energy Equivalent Speed, (EES), artificial intelligence (AI), convolutional neural networks (CNN), PC-Crash, estimation

PREDIKCIJA EES VREDNOSTI U SUDARIMA VOZILA PRIMENOM VEŠTAČKE INTELIGENCIJE

REZIME: Energija ekvivalentne brzine (EES), koja se tokom sudara utroši na rad deformacije, predstavlja važan parametar za određivanje udarne brzine vozila. Ova vrednost se može izračunati, ali njeno određivanje zahteva podatke o dubini deformacije vozila duž cele širine oštećenog područja, koji su najčešće dokumentovani samo fotografijama. Zbog toga se u analizi saobraćajnih nezgoda vrednost EES-a obično procenjuje subjektivno od strane veštaka, na osnovu poređenja fotografija snimljenih tokom ili nakon saobraćajne nezgode sa referentnim slikama iz elektronskih EES kataloga. Primena informacionih tehnologija (IT) u analizi saobraćajnih nezgoda omogućila je primenu veštačke inteligencije (AI) za predviđanje vrednosti EES-a na osnovu podudarnosti između

[1] *Zoran Papić, University of Novi Sad, Faculty of technical sciences, Department for traffic, Dositej Obradović Sq. 6, 21000 Novi Sad, z.papic@uns.ac.rs, https://orcid.org/0000-0003-1264-0913*
[2] *Nenad Saulić, University of Novi Sad, Faculty of technical sciences, Department for traffic, Dositej Obradović Sq. 6, 21000 Novi Sad, nenadsaulic@gmail.com, https://orcid.org/0000-0002-1151-6737*
[3] *Milja Simeunović, University of Novi Sad, Faculty of technical sciences, Department for traffic, Dositej Obradović Sq. 6, 21000 Novi Sad, mlekovic@uns.ac.rs, https://orcid.org/0000-0001-9650-2635*

oštećenja uočenih na vozilu koje je predmet analize i oštećenja dokumentovanih na sličnim vozilima u EES katalozima. U ovom radu predstavljena je analiza mogućnosti i pouzdanosti alata zasnovanih na veštačkoj inteligenciji za procenu vrednosti EES-a na vozilima, korišćenjem alata integrisanih u softversko okruženje PC-Crash, koji se zasnivaju na konvolucionim neuronskim mrežama (CNN).

KLJUČNE REČI: Ekvivalent brzine izgubljene na deformacioni rad (EES), veštačka inteligencija (AI), konvolucione neuronske mreže (CNN), PC Crash, procena

INTRODUCTION

Vehicle collisions are the most common type of road traffic accident. One of the most complex problems in the investigation of traffic accidents is determining the directions of vehicle movement and their speeds at the moment of the collision. Methods for determining collision speeds are based on fundamental physical laws, primarily the laws of conservation of linear momentum and energy.

The energy method assumes that the total kinetic energy of the vehicles at the moment of collision is equal to the sum of the energy dissipated during and after the collision. This includes the energy absorbed through vehicle deformation, the remaining kinetic energy and the energy dissipated in the form of vibrations, sound and heat. An approach to establish a relationship between crash speed and the extent of vehicle deformation resulting from an impact with a stationary, non-deformable obstacle was developed based on the results of crash tests that began to be conducted extensively in the USA during the second half of the 1960s. Increasing attention to vehicle passive safety, particularly following criticism of the safety of vehicles of that period by the American lawyer and journalist Nader (1968), contributed to the development of this approach. Mackay (1968) formalised this concept by introducing the term 'Equivalent Barrier Speed' (EBS), which enables the comparison of vehicle damage observed in real-world traffic accidents with damage produced under controlled crash-test conditions. Based on the analysis of crash tests, it was determined that most of the vehicle's kinetic energy at the moment of impact is dissipated through plastic deformation, that is, through deformation work, while the remaining portion of the energy is associated with the motion of the vehicle during the post-collision phase. The kinetic energy of the vehicle immediately after the collision, at the beginning of the restitution phase, depends on its structural characteristics and, consequently, on the elasticity of the collision, which is characterized by the coefficient of restitution, k. The coefficient of restitution is defined as the ratio of the relative velocity of the vehicles after the collision, at the end of the restitution phase, to their relative velocity at the moment of impact.

$$k = \frac{V_2' - V_1'}{V_1 - V_2} \tag{1}$$

where:

V_1, V_2 – vehicle impact speeds;
$V_{1'}$, $V_{2'}$ - vehicle speeds at the and of the restitution phase.

Research has shown that, in real-world traffic accidents, the coefficient of restitution typically ranges from 0.05 to 0.3, with higher values corresponding to more elastic collisions.

In order to establish a relationship between the equivalent speed corresponding to the energy dissipated through vehicle deformation during an impact with a non-deformable obstacle (EBS) and real-world collisions involving two vehicles, Burg & Zeidler (1980) introduced the concept of EES (Energy Equivalent Speed). According to the ISO/DIS 12353-1:1996 standard, EES is defined as the speed at which a vehicle would have to collide with a stationary, non-deformable obstacle to absorb an amount of deformation energy equivalent to that associated with the damage observed on the vehicle.

$$EES = EBS \cdot \sqrt{1 - k^2} \tag{2}$$

The EES value of a vehicle involved in a collision can be calculated with varying degrees of simplification; however, such a calculation requires data on the depth and shape of the vehicle deformations, the vehicle stiffness coefficient, vehicle mass, and other relevant parameters. In practice, however, vehicle deformations resulting from traffic accidents are often not adequately documented, and measurements of the deformed areas that could be used to calculate the EES value are therefore unavailable. Consequently, the calculation of vehicle impact speeds using the energy method relies to a large extent on the expert's visual assessment of the EES value based on the observed vehicle damage.

To investigate the reliability of EES estimates based on damage visible in photographs, Papić et al. (2022) asked 23 experts in traffic accident analysis to estimate the EES values for eight damaged vehicles. The results showed

that the accuracy of the estimates depended largely on the magnitude of the vehicle impact speed. For the lower EES values (10 and 20 km/h), the estimates did not differ statistically significantly from the actual EES values. This result was expected, given the relatively low severity of the vehicle damage. In contrast, a statistically significant difference between the actual and estimated EES values was found for EES values in the range of 40–80 km/h. Within this range, the respondents predominantly tended to underestimate the EES values, which is consistent with the findings reported by Spek (2017).

The PC-Crash software package includes the DSD Recon Data database, an electronic catalog that provides EES values based on expert assessments by specialists in the field of vehicle collisions. The catalog classifies vehicles according to make, type, model, year of manufacture, mass, and location of damage, and provides expert estimates of the vehicle speed lost through deformation during a collision.

The reliability of the estimated EES values in this database is indicated by circular symbols displayed in green, yellow, or red. A green symbol indicates that the estimated EES value can be considered reliable evidence when determining the vehicle's collision speed. A yellow symbol indicates that the estimated value may be considered sufficiently reliable, but should be verified using additional parameters, such as the depth of vehicle deformation, the vehicle stiffness coefficient, and other relevant data. According to Goertz (2018), a red symbol indicates a wide range of estimated EES values and, consequently, that the value should not be considered fully reliable when determining the collision speed in a traffic accident reconstruction.

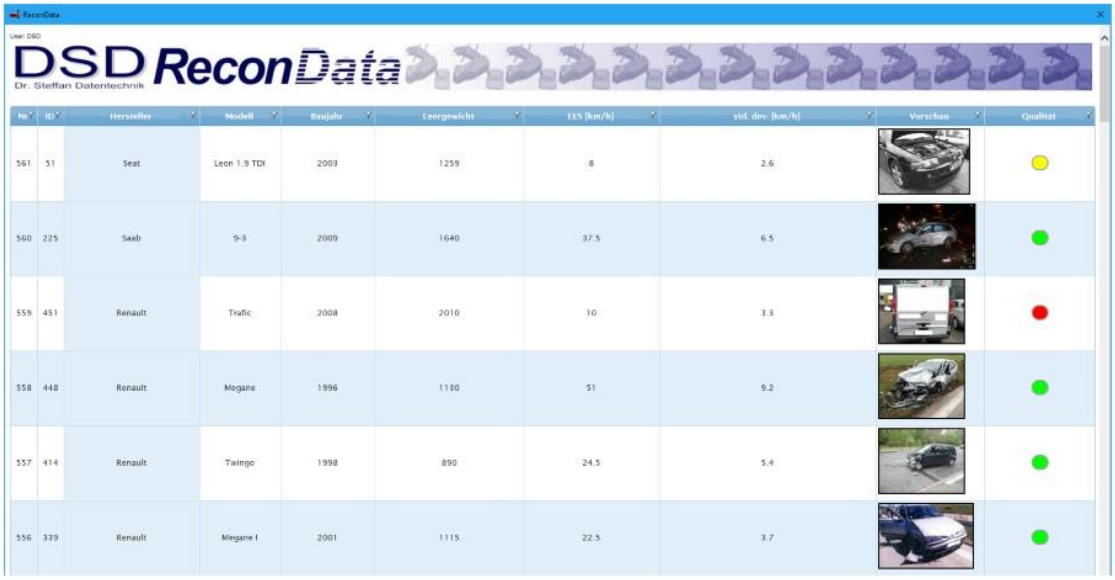


Figure 1 EES value database in the PC-Crash software package

	Fahrzeug 1	Fahrzeug 2	Fahrzeug 3
Hersteller:	Audi	Hyundai	
Modell:	A6 Avant TDI	Getz 1.4	
Baujahr:	2008-01-01	2008-01-01	
Leergewicht [kg]:	1825	1100	
ID:	721097	721098	0

Fragestellung:
EES

Name	EES 1	EES 2		Energieverteilung	
1	45-55	70-80	km/h	42%	58%
2	55-57	63-67	km/h	55%	45%
3	57-64	62-68	km/h	59%	41%
4	35-40	50-55	km/h	46%	54%
5	40-50	40-50	km/h	62%	38%
6	45-50	55-65	km/h	51%	49%
7	40-50	45-55	km/h	57%	43%
8	35-40	38-43	km/h	59%	41%
9	45-55	60-65	km/h	51%	49%
10	45-55	50-60	km/h	58%	42%
11	30-40	35-45	km/h	56%	44%
12	48-53	65-70	km/h	48%	52%
13	45-55	60-70	km/h	50%	50%
14	37-43	47-53	km/h	51%	49%
15	52-60	60-70	km/h	55%	45%
16	30-35	55-65	km/h	33%	67%
17	45-55	75-85	km/h	39%	61%

Min/Max	30-64	35-85	km/h
Mittelwert	46.6	58.7	km/h
Median	50	60	km/h
Standardabweichung	7.9	11.3	km/h
Def-Energie Median	176	152.8	kJ
Sigma/Median Energieverhältnis	34	41	%
Qualitätsindikator			

Figure 2 Expert assessment of the EES value for a case in the PC-Crash database

Artificial intelligence (AI) is increasingly being applied in the field of traffic accident reconstruction. One of the aspects of AI application in the analysis of traffic accidents, particularly vehicle collisions, involves estimating the equivalent speed of a vehicle dissipated through deformation work, i.e., the EES value. In the analysis of vehicle collisions, AI can be used to obtain, based on photographs taken during the accident scene investigation or after the traffic accident, as well as under controlled conditions, information on the make and type of the vehicle involved in the traffic accident, the classification and type of collision, as well as the EES value corresponding to the vehicle's deformations and damage.

FUNDAMENTALS OF *AI* AND TERMINOLOGY

The term artificial intelligence (AI) was introduced in the 1950s and can be broadly defined as the development of intelligent machines, particularly computer programs designed to solve problems that have traditionally required human intelligence and decision-making. In this context, artificial intelligence involves the use of computer-based systems to process information and perform tasks by learning from data and applying knowledge acquired through previous experience.

Machine learning (ML) is a subset of artificial intelligence that encompasses techniques enabling computers to learn from available data and derive conclusions based on:

- a database containing numerical, textual, or image-based data;
- mathematical models, expressed as functions, used to generate predictions;
- model adjustment through parameter optimization based on the detection and magnitude of prediction errors;
- model evaluation based on tests using data that were not used to develop the model.

Artificial neural networks (ANNs) are interconnected systems of nodes based on simplified models of biological neurons in the human brain. The main components of an ANN are:

- **Input parameters (inputs)** – each input represents a specific piece of information expressed as a numerical value, which may be any real number;
- **Connections (weights)** – each connection between two neurons is assigned a numerical weight that represents the strength or importance of that connection. Each neuron in a given layer receives information from the neurons in the preceding layer and passes the processed information to the next layer. As the information propagates through the network, previously hidden features of the input data are extracted and combined to generate new representations;
- **Summation function** – combines the input values and the corresponding connection weights to calculate a weighted sum, which is then used as the input to the activation function;
- **Activation function** – determines the output of a neuron based on the weighted sum of its inputs. Similar to a biological neuron, which generates a signal when a certain activation threshold is reached, an artificial neuron produces an output when the activation function is applied to the weighted sum of its inputs.

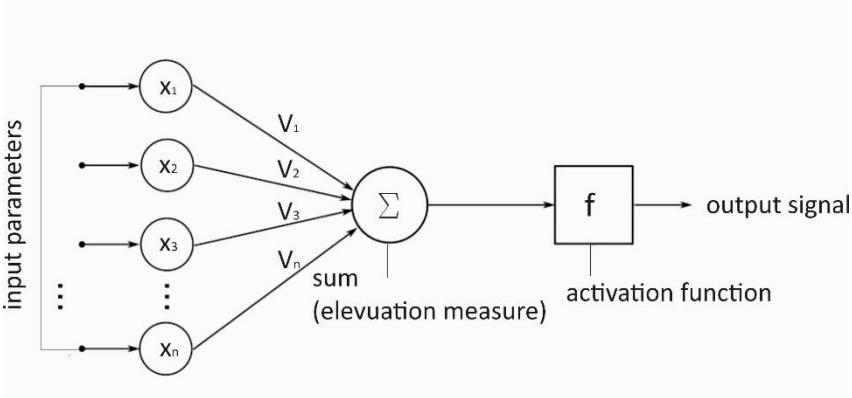


Figure 3 Architecture of an artificial neural network (ANN)

Deep learning (DL) is a subset of machine learning that uses multilayer artificial neural networks to solve complex problems by learning increasingly abstract representations from data. As the number of hidden layers increases, deep neural networks can achieve high levels of accuracy in tasks such as object detection, speech recognition, and the translation of written or spoken language. Deep learning techniques enable the automatic learning, extraction, and transformation of features from datasets, such as images, videos, and text, without the need to explicitly define rules or manually program the features used for these tasks.

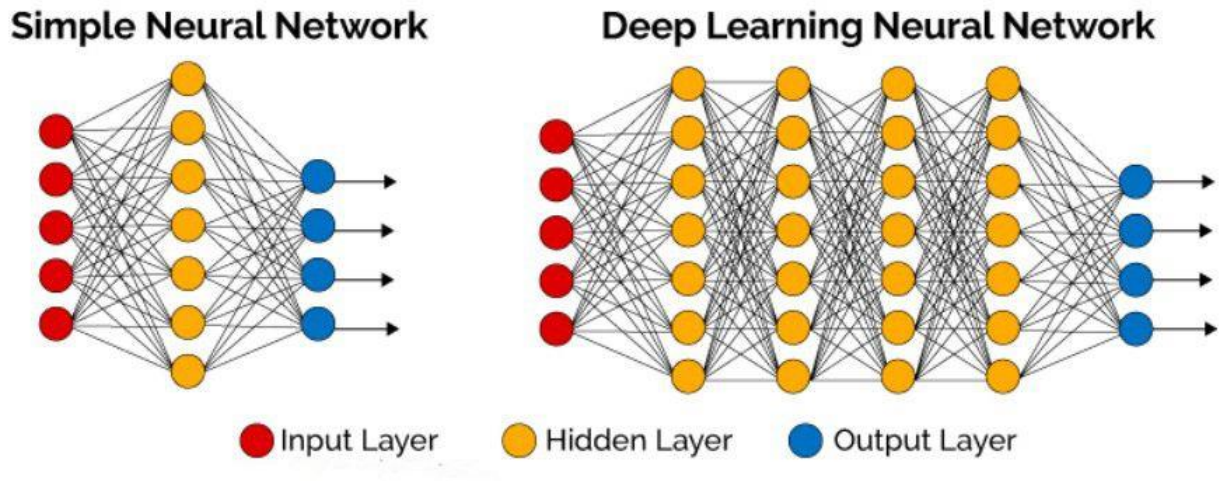


Figure 4 Difference between a simple artificial neural network (ANN) and a deep neural network (DL)

Unlike simple neural networks, which are less complex and often require greater knowledge of the relevant data features for feature selection and engineering, deep neural networks can automatically learn relevant features from raw data, eliminating the need for predefined feature selection. They can also automatically optimize model parameters during the training process.

Convolutional Neural Networks (CNNs) are deep artificial neural networks primarily used for image processing and classification. They can classify images based on their visual content, group visually similar images, and detect and recognize objects within an image. The application of CNNs has enabled their practical use in various traffic-related tasks, including vehicle recognition, traffic sign and signal recognition, and identification of the surrounding environment relevant to the analysis of a particular traffic event. More recently, CNNs have also been applied to the recognition of vehicle drivers.
In machine learning, different learning approaches are generally classified into three main categories: **supervised learning, unsupervised learning, and reinforcement learning**.

Supervised learning involves a dataset in which each example is associated with a known output label, which may be either discrete or continuous. In this approach, the learning algorithm is trained using labeled data, where the desired output is known for each input example. The model learns the relationship between the input data and the corresponding output labels and uses this relationship to make predictions for previously unseen data. Supervised learning includes techniques such as linear regression, logistic regression, and classification using decision trees.

APPLICATION OF DEEP NEURAL NETWORKS FOR VEHICLE RECOGNITION AND EES ESTIMATION

Artificial intelligence based on deep convolutional neural networks (CNNs) has enabled the application of these methods to increasingly specialized problems across various fields. In order to achieve better performance, there has been a need to develop deeper neural networks. However, in practice, it has been observed that increasing network depth beyond a certain number of layers (approximately 20–30) does not necessarily improve performance and may, in some cases, lead to performance degradation.

In order to overcome this problem, an approach based on learning residual functions was developed, in which the network does not learn the complete transformation of the input data but only the deviations (residuals) from the identity function. This concept enabled the efficient training of very deep neural networks, with more than 100 layers, resulting in more stable learning and improved accuracy of the output.

ResNet-152 is a deep neural network designed for image processing and consists of 152 layers. It was developed by Microsoft Research in 2015 and represents one of the key architectures in the development of modern artificial intelligence for computer vision. The network can be used for object recognition in images, medical diagnostics based on X-ray and MRI images, the development of autonomous vehicles, video analysis, and AI-based systems for assessing vehicle damage, among other applications. Thus, based on the previously trained ResNet-152 network using the Stanford Cars Dataset, a vehicle recognition system was first developed. According to Krause et al. (2013), the dataset contains 16,185 images covering 196 different vehicle models. Using this network, an accuracy of 88.7% was achieved in recognizing the vehicle manufacturer and model.

PC Crash EES CNN

Since the results achieved in vehicle manufacturer and model recognition met expectations, the same approach was applied to the classification of EES values in newer versions of the PC-Crash software (version 15.0 and later), as part of the integration of machine learning methods with vehicle damage databases. In this context, an AI-based tool was developed to estimate the EES value of a vehicle based on photographs of its damage. For training purposes, photographs of damaged vehicles from the DSD ReconData EES catalog developed by Moser and Steffan (2019) were used. The catalog contains approximately 4,000 photographs, with EES values ranging from 5 to 85 km/h. The best results are obtained from photographs in which the depth of the vehicle deformation is clearly visible.

As an example of the user interface used for EES-CNN analysis, photographs and data collected during the DSD workshop were used. These data were obtained as part of crash tests conducted in 2018, at a time when the results of these tests had not yet been included in the databases used for deep learning. The test involved an “OPEL ZAFIRA” passenger car, with a mass of 1395 kg, colliding with the rear of a stationary “MAN” truck, with a mass of 10754 kg, in a full-overlap collision at a speed of 70.8 km/h. Figure 5 shows the speed profile of the “OPEL ZAFIRA” during the test.

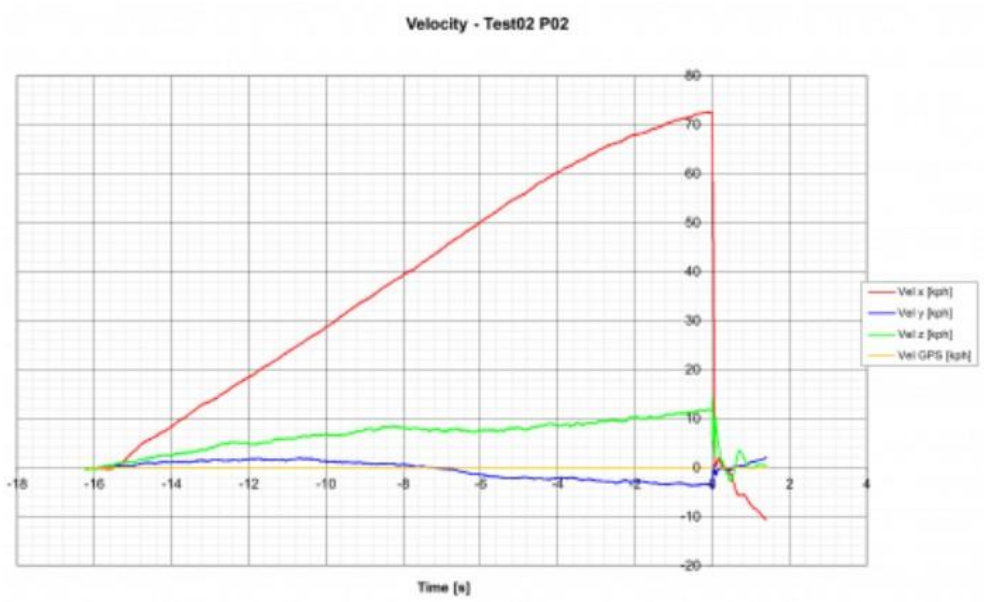


Figure 5 Speed profile of the “OPEL” passenger car during the collision with the “MAN” truck

The position of the vehicle at the moment of collision and immediately thereafter is shown in Figures 5 and 6.



Figures 6, 7 Positions of the “OPEL” passenger car and the “MAN” truck at the moment of collision and after coming to a stop

Given that the truck was displaced forward by approximately 1–1.5 m as a result of the collision, and that part of the kinetic energy of the “OPEL” passenger car at the moment of impact was also dissipated through deformation of the rear part of the truck, the EES value of the “OPEL” was lower than its impact speed and was realistically estimated to be in the range of 60–65 km/h. After the collision, the "OPEL" car was photographed in detail from several angles. The selected photographs used for the analysis of the EES-CNN values, showing the damage to the front of the vehicle, are presented in Figures 7 and 8.




Figures 8, 9 Front-end damage to the "OPEL" car following the collision with the "MAN" truck

After opening the EES-CNN user window, if the vehicle is selected for analysis in the PC-Crash program, its make and model are displayed in the upper-left corner. Below this, there is an option to import photographs showing the damage to the vehicle. For the purpose of EES analysis, multiple photographs of the vehicle damage, taken from different angles, can be uploaded. Once a photograph has been uploaded, a histogram showing the estimated EES values for that particular photograph, together with the corresponding estimation reliability, is displayed in the window on the right.

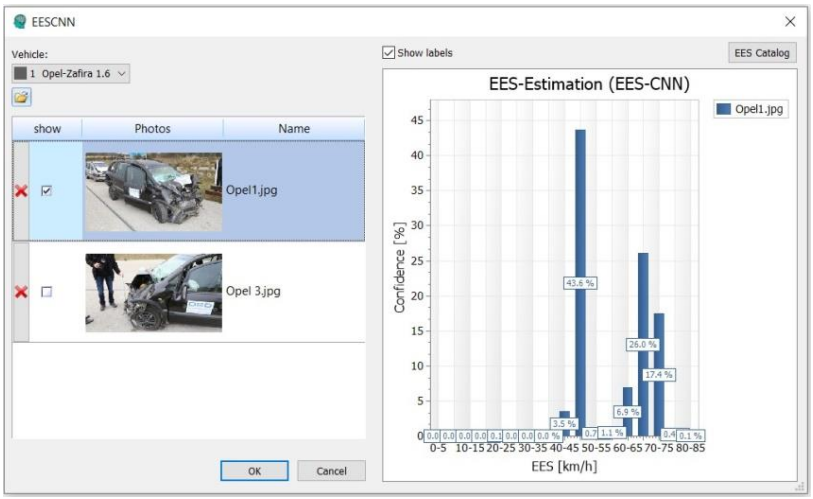


Figure 10 EES-CNN assessment of the damage to the "OPEL" car shown in Figure 7



Figure 11 EES-CNN assessment of the damage to the "OPEL" car shown in Figure 8

As can be seen in Figure 9, where the damage to the "OPEL" car was recorded at a slight angle relative to the front-right corner of the vehicle, the EES interval of 45–50 km/h was identified as the most reliable estimate, with a reliability of 43.6%. If the estimated EES interval of 60–75 km/h, which encompasses the actual EES value, were considered as a whole, the reliability of the estimate would be approximately 51%.

In Figure 10, where the damage to the vehicle was recorded from the left side and the deformation depth can be observed more clearly, the EES interval of 55–60 km/h was identified as the most reliable estimate, with a reliability

of 39.5%. However, if the EES interval of 55–75 km/h, which encompasses the actual EES value, were considered as a whole, the reliability of the assessment would be approximately 68%.

RELIABILITY OF EES VALUE ESTIMATION: AI VERSUS EXPERT ASSESSMENT

According to Papić et al. (2022), a total of 23 respondents participated in the assessment of the reliability of expert EES value estimation based on photographs of vehicle damage, 22 of whom are actively engaged in traffic accident reconstruction and expert examination. The respondents were provided with questionnaires in which, among other tasks, they were asked to subjectively estimate the EES value for eight vehicles. For each vehicle, two photographs showing the damage caused in collisions under controlled conditions were provided. The photographs were selected from the Crash Test Database included in the PC-Crash software package. Photographs showing vehicle damage resulting from collisions with a stationary, non-deformable obstacle were selected for the analysis. Under such collision conditions, practically all of the vehicle's kinetic energy at the moment of impact is dissipated through deformation work, i.e.:

$$V_s \approx EBS \approx EES \tag{3}$$

Of all EES values estimated by the respondents who participated in the study, 32.6% were correctly estimated, while 67.4% were incorrectly estimated. Most of the incorrect estimates (53.8%) were lower than the actual EES values, whereas the remaining 13.6% represented an overestimation. It is important to note that an estimate was considered correct if it deviated by no more than ±5 km/h from the actual EES value.

The same photographs used in the aforementioned study were also used to analyze the reliability of EES value estimation using artificial intelligence, specifically the EES-CNN tool integrated into the PC-Crash software package. Since the reliability of the EES estimates provided by this tool is expressed as a percentage in the form of a histogram, with a certain degree of dispersion, only the 5 km/h-wide speed intervals with the highest reliability percentage were considered in the analysis.

Based on the conducted analysis, it was determined that the reliability of the EES estimates ranged from 48.5% to 99%. However, a high reliability percentage assigned by the AI system does not necessarily mean that the estimated EES value is accurate. If the same criterion used in the study of expert EES assessment is applied, namely, a deviation of ±5 km/h from the actual EES value, the following conclusions can be drawn:

- in five cases, the EES values estimated by EES-CNN were within ±5 km/h of the actual EES values;
- in one case, the estimated EES value deviated from the actual value by more than 15 km/h;
- in two cases, the estimated EES values deviated from the actual values by more than 20 km/h.

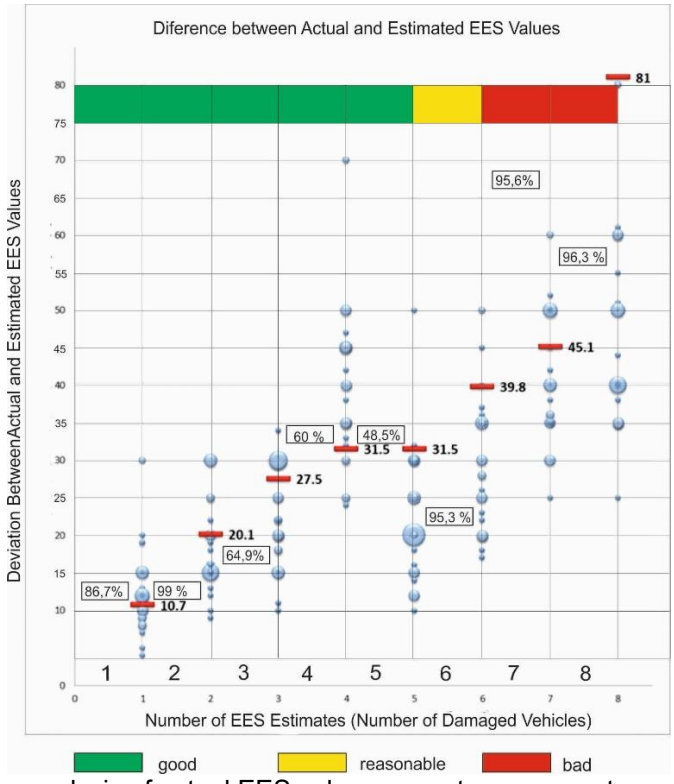


Figure 12 Comparative analysis of actual EES values, expert assessments, and EES-CNN estimates

Based on the conducted analysis, it can be concluded that AI provides greater consistency in assessments, while the expert approach enables a deeper understanding of the specific circumstances of the accident. Therefore, the optimal approach lies in combining these two methods, with AI tools serving as a rapid and objective support, while the final assessment should be based on a comprehensive expert analysis.

CONCLUSION

Based on the theoretical considerations presented and the analyses conducted, it can be concluded that EES (Energy Equivalent Speed) represents one of the key parameters in the reconstruction of traffic accidents, particularly within the framework of energy-based methods for estimating vehicle crash speeds. Although the EES value can be calculated based on physical laws and measurements of vehicle deformation, in practice, this procedure is often limited by the lack of precise data. Consequently, a significant proportion of EES assessments relies on visual evaluation by experts.

The research results show that the accuracy of expert assessments depends on the extent of vehicle damage, with assessments being more reliable for lower EES values, while higher EES values tend to be underestimated. On the other hand, the application of modern AI methods, particularly convolutional neural networks (CNNs), enables the automated analysis of vehicle damage photographs and provides more stable and consistent results with a certain degree of reliability. However, the analyzed AI-based approach also has certain limitations, primarily related to image quality, the camera angle, and the inability to directly assess internal structural damage to the vehicle. Therefore, its results should not be regarded as definitive, but rather as supplementary information within the overall accident analysis process.

The comparative analysis indicates that AI systems provide greater consistency in EES assessments, while the expert approach, despite its inherent subjectivity, enables a deeper understanding of the specific circumstances of an accident.

In this context, the optimal approach to EES estimation involves integrating artificial intelligence with expert knowledge. AI tools can be used as rapid and objective support during the initial assessment, while the final evaluation should be based on a comprehensive expert analysis, thereby improving the reliability and objectivity of the traffic accident reconstruction process. From a practical perspective in traffic accident reconstruction and forensic analysis, this combination of methods represents a realistic and applicable approach to everyday expert practice.

Considering its practical application, it can be expected that further research in the field of AI-based vehicle damage recognition and assessment will focus on expanding and diversifying training datasets, incorporating information on the geometry and depth of vehicle deformations, and integrating multimodal data sources, such as photographs, 3D images, and vehicle technical specifications. These developments could contribute to improving the accuracy and robustness of EES estimation under real-world traffic accident conditions.

ACKNOWLEDGMENTS

The results presented in this paper are part of the research conducted within the project “Researching trends in the development of sustainable transport and logistics systems”, established by the Department of Traffic Engineering, Faculty of Technical Sciences, University of Novi Sad, Republic of Serbia.

REFERENCES

Burg, H., & Zeidler, F. (1980). EES - ein Hilfsmittel zur Unfallrekonstruktion und dessen Auswirkung auf die Unfallforschung. *Der Verkehrsunfall*, 4, 75-78.

Goertz, M. (2018). *Modell zur Bestimmung von Deformationsenergien an Fahrzeugen nach Verkehrsunfaellen*, Dissertation. University of Żilina.

Krause, J., Stark, M., Deng, J., & Fei-Fei, L. (2013, 2-8 December), 3D Object Representations for Fine-Grained Categorizatio. *4th International IEEE Workshop on 3D Representation and Recognition (3dRR-13*). Sydney, Australia. https://doi.org/10.1109/ICCVW.2013.77

Mackay, M. (1968). Injury and collision severity, *SAE Technical Paper*, 680779, 3108-3113. https://doi.org/10.4271/680779

Moser, A., & Stefan, H. (2019). Artifical Inteligence (AI) in Accident Reconstruction. EVU Congress, Proceedings, Barcelona.

Nader, R. (1965). *Unsafe at any speed*. New York, Grossman.

Papić, Z., Bogdanović, V., Simeunović, M., Saulić, N., & Jović, A. (2022, 19-21 Maj). Pouzdanost procene EES vrednosti u analizi sudara vozila. *Savetovanje-Saobraćajne nezgode, Zbornik radova*, Zlatibor.

PC-Crash 15.1. (2019). A Simulation program for Vehicle Accidents 15.1 - Operating Manual.

Spek, A. (2017). Collaborative study on the estimation of EES-values, EVU Congress, Proceedings, Haarlem, The Netherlands.