

Defining Energy Indicators for Impact Identification on Aerospace Composites: A Physics-Informed Machine Learning Perspective*

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ABSTRACT

Energy estimation is critical to impact identification on aerospace composites, where low-velocity impacts can induce internal damage that is undetectable at the surface. Current methodologies for energy prediction are often constrained by data sparsity, signal noise, complex feature interdependencies, non-linear dynamics, massive design spaces, and the ill-posed nature of the inverse problem. To address these challenges, this study introduces a physics-informed framework that embeds domain knowledge into machine learning through a dedicated input space. The approach combines observational biases, which guide the design of physics-motivated features, with targeted feature selection to retain only the most informative indicators. Features are extracted from time, frequency, and time-frequency domains to capture complementary aspects of the structural response. A structured feature selection process integrating statistical significance, correlation filtering, dimensionality reduction, and noise robustness ensures physical relevance and interpretability. Exploratory data analysis further reveals domain-specific trends, yielding a reduced feature set that captures essential dynamic phenomena such as amplitude scaling, spectral redistribution, and transient signal behaviour. Together, these steps produce a compact set of energy-sensitive indicators with both statistical robustness and physical significance, resulting in impact energy predictions that remain interpretable and traceable to measurable structural responses. Using this optimised input space, a fully-connected neural network is trained and validated with experimental data from multiple impact scenarios, including pristine and damaged states. The resulting model demonstrates significantly improved impact energy prediction accuracy, reducing errors by a factor of three compared to conventional time-series techniques and purely data-driven models. Overall, the framework advances predictive performance, interpretability, and diagnostic confidence by embedding domain-knowledge insights through feature-level design. Its strength lies in the integration of observational biases with targeted feature selection for an effective impact identification method.

1. Introduction

Aerospace composite structures are susceptible to Barely Visible Impact Damage (BVID), which poses a critical threat to both structural integrity and operational safety. These internal damages are typically undetectable by conventional visual inspection and can significantly degrade load-bearing capacity [82, 11]. To mitigate these risks, Structural Health Monitoring (SHM) systems have been developed to capture dynamic responses using embedded sensors. These systems enable the estimation of impact energy and the detection of internal damage, supporting timely maintenance, enhancing operational reliability, and proposing design improvements [36, 91, 87].

A central challenge in this context is the reconstruction of impact energy from measured responses, which constitutes an ill-posed inverse problem. The relationship between sensor signals and unknown impact conditions is typically non-unique, highly sensitive to noise, and underdetermined. These difficulties intensify under practical constraints, such as sparse sensor layouts, uncertainties in measurements, and non-linear structural behaviour at high

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excitation levels. Consequently, conventional methods frequently produce unstable or non-physical estimates unless constrained by regularisation or supported by computationally intensive formulations [90, 55]. To ensure reliable performance under these conditions, estimation strategies must effectively manage incomplete and noisy data, preserve numerical stability, and support real-time execution within embedded systems.

Research efforts sought to address these challenges using numerical, analytical, data-driven, and hybrid approaches. In the numerical and analytical domains, Liu and Wang [55] developed a finite-element model for woven laminates subjected to low-velocity impact. Their model reconstructed force histories with reasonable accuracy but required intensive computation and relied exclusively on simulated virtual accelerations. Correias et al. [14] introduced an analytical spring-mass model for stiffened panels that shows strong agreement with numerical simulations. However, the model employed simplified loading assumptions, idealised boundary conditions and lacked experimental validation.

Data-driven methods have also been employed to model complex and non-linear relationships between structural responses and unknown impact conditions. Tabian et al. [83] employed a Convolutional Neural Network (CNN) to localise and quantify impacts on composite structures. Similarly, Ghajari et al. [77] successfully reconstructed impact force histories from time-series data. Although these approaches exhibit effectiveness in controlled environments, they typically demand large, high-quality datasets and struggle with generalisation to new or noisy scenarios. Their dependence on data representativeness and low interpretability further constrained practical deployment.

Additional developments have explored probabilistic and hybrid techniques. Yan et al. [86] introduced a Bayesian regularisation framework combined with an unscented Kalman filter to improve noise robustness for impact identification. Although the method improved stability, it remained sensitive to sensor configuration and limited to low-energy regimes. Huang et al. [37] employed transfer learning in a deep learning model, reaching acceptable accuracy but requiring extensive tuning and access to reference force histories. Zhang et al. [89] integrated experimental testing with high-fidelity simulations on honeycomb panels, yielding detailed insights but incurring high computational costs and sensitivity to parameterisation. Despite their contributions, probabilistic and hybrid methods remain computationally demanding, difficult to scale, and dependent on sensor configurations and reference data, which limits their practical adoption.

Overall, these approaches highlight critical gaps in existing literature. Many methods rely on idealised boundary conditions or simplified impact scenarios, which reduce the reliability of the estimation and limit generalisation. Others depend heavily on large datasets and remain vulnerable to noise, sensor placement, and parameterisation. In addition, the ill-posed nature of the inverse problem, combined with low interpretability, limits its implementation in operational environments. Above all, most approaches neglect the explicit incorporation of physical insight into the input space. As a result, models often fail to distinguish between measurement artefacts and the actual system dynamics, thereby compromising both predictive accuracy and physical relevance.

In response to these limitations, Physics-Informed Machine Learning (PIML) [44, 16, 45], also referred to as Physics-Enhanced Machine Learning (PEML) [49, 13] or grey-box modelling [15, 32], has emerged as a promising approach. By embedding physical knowledge into data-driven frameworks, PIML improves robustness, interpretability, and generalisation. Importantly, it reflects the knowledge–data balance, where physical insight can compensate for limited or noisy data. Although this strategy has been applied in other engineering domains, its use for impact identification in aerospace composites remains unexplored. More broadly, input space design has received limited attention across disciplines, despite being a critical step in linking measurement signals to governing dynamics and ensuring reliable energy estimation.

This study addresses this gap through a hybrid framework that integrates observational bias within a PIML architecture. The framework builds on the principle that measurement signals carry information about the input excitation [65]. Observational bias is then addressed by utilising this information to construct the input space from physics-motivated features that capture the structural dynamics. These features form a multi-domain candidate set extracted from time, frequency, and time–frequency descriptors. Each domain contributes complementary information, and together these descriptors provide a complete and balanced characterisation of the impact event that no single domain can achieve.

Although prior studies in acoustic emission and impact analysis [63, 79, 46, 71] confirm the diagnostic value of multi-domain descriptors, they also demonstrate their sensitivity to propagation path effects, attenuation, non-linearities, and noise. Given these drawbacks, the framework applies targeted feature selection to retain only the most relevant and robust descriptors. This process yields a compact, balanced set of energy-sensitive features that is both physically meaningful and efficient. The refined feature subset forms the optimised input space for a Fully Connected Neural Network (FCNN) trained to estimate impact energy. Taken together, the strength of the framework lies not in

observational bias alone but in its integration with targeted feature selection. This integration constitutes the central contribution of the study, providing a physically meaningful and robust basis for energy prediction under imperfect measurement conditions.

Use-case The framework is applied to a dataset obtained from intermediate-mass impact tests on a square composite panel, covering multiple impact locations and energy levels. The dataset replicates conditions typical of in-service SHM applications, characterised by low signal quality, limited data availability, and loading scenarios both below and above the damage onset. This configuration provides a realistic benchmark to assess feature robustness and verify the effectiveness of the proposed input space design.

Contribution The main contributions of this study are:

- Achieves accurate impact energy estimation under limited and unbalanced datasets, outperforming conventional methods;
- Ensures interpretability by linking observed structural responses to the underlying dynamic phenomena;
- Provides explainability and transparency through the selection of features that capture structural behaviour and by demonstrating how the input space can be systematically improved;
- Maintains robustness under noisy measurement conditions;
- Offers practicality through a simple yet efficient feature-level design;
- Enables feature ranking by assigning quantitative scores that support objective performance comparison and selection.

This paper is structured as follows. Section 2 outlines the fundamental principles of physics-informed machine learning, with emphasis on observational bias in input space design. Section 3 presents the feature extraction and selection methodology, detailing each stage of the proposed framework. Section 4 presents the experimental and numerical datasets used for feature evaluation and model validation. Section 5 reports the results and assesses model performance. Finally, Section 6 summarises the key findings and identifies directions for future research.

2. Principles of physics-informed machine learning

Physics-Informed Machine Learning (PIML) offers a robust alternative for impact energy estimation when data are limited and physical models are incomplete or costly to simulate [45, 43]. Karniadakis et al. [44] identified four principal strategies for embedding physics into machine learning models: (1) *observational bias*, ensuring training data reflect physical laws or using advanced augmentation; (2) *learning bias*, designing loss functions and constraints that enforce physical conformity; (3) *inductive bias*, adapting model architectures to embed prior physical assumptions; and (4) *discrepancy bias*, including known terms from partial physics-based models to guide learning.

Within this classification, the four bias strategies provide a useful framework for categorising physics-informed learning, but they are not mutually exclusive, and effective PIML does not require all of them. This study, therefore, concentrates on observational bias by embedding prior physical knowledge into the input space through physics-motivated signal features for impact energy estimation. This approach remains practical because it avoids intrusive model constraints and costly simulations, while still capturing the essential behaviour of the system. In doing so, it improves predictive accuracy and generalisation, yet remains computationally efficient and adaptable.

3. Feature extraction and selection method

The proposed feature extraction and selection method designs an optimised input space through physics-guided feature extraction, statistical evaluation, and ranking and selection strategies, as illustrated in Figure 1. In this framework, the term *input space* consistently refers to the selected set of features extracted from sensor signals and used as input to an FCNN for impact energy prediction.

In the first step, candidate features $x^{(0)}$ are extracted to capture the dynamic behaviour of the structure under impact. This initial feature set is grounded in structural dynamics and composite material behaviour, ensuring that descriptors

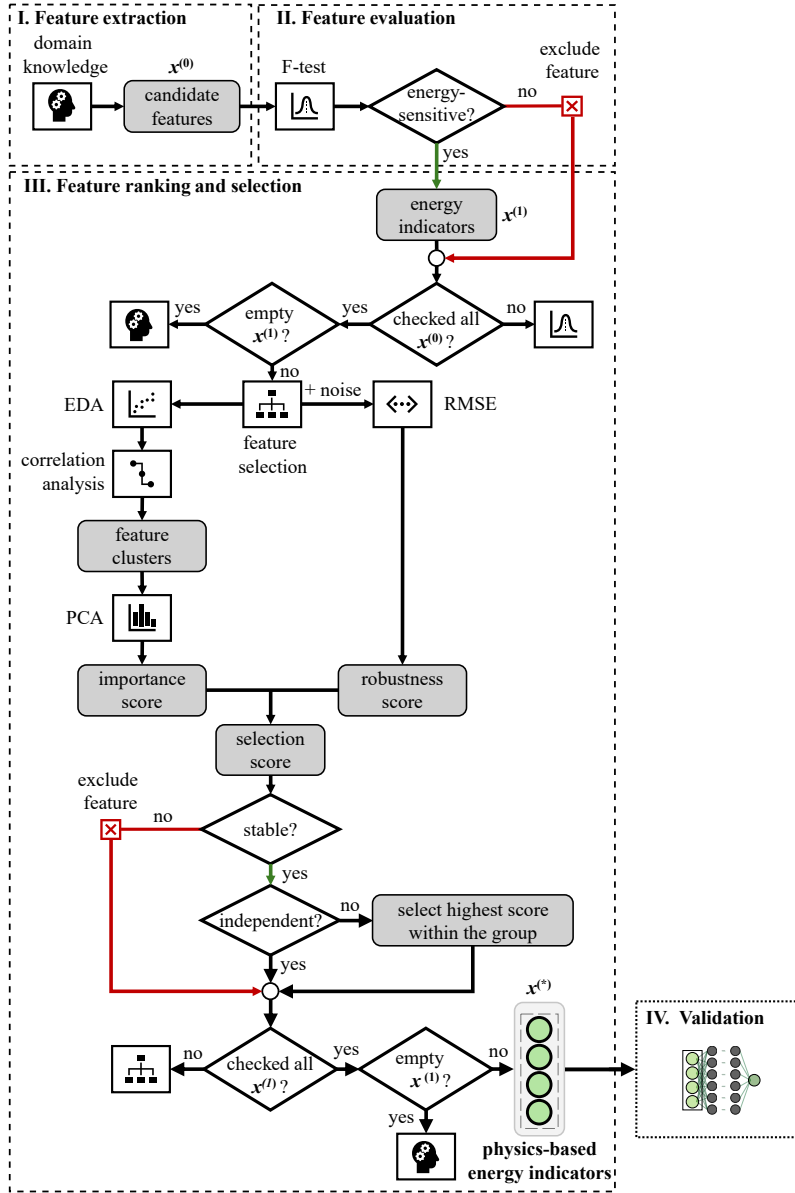


Figure 1: Framework for defining a physics-motivated input space. Feature candidates $x^{(0)}$, energy-sensitive features $x^{(1)}$, and physics-based energy indicators $x^{(*)}$. Black arrows: processing paths; red arrows: discarded descriptors; and green arrows: selected features.

retain physical meaning. To represent complementary aspects of the response, features are derived from the time, frequency, and time–frequency domains, as detailed in the following section. This multi-domain design preserves physical traceability and yields potential energy indicators that provide a consistent basis for subsequent evaluation.

The second step evaluates whether candidate features $x^{(0)}$ respond to variations in impact energy by testing their statistical sensitivity through an F-test. Features that do not show significant variation are discarded, leaving a reduced subset of energy indicators $x^{(1)}$. A feedback loop addresses cases where no features pass the statistical test by returning to the extraction stage, where domain knowledge is applied to define new descriptors. The framework assumes that sensors capture relevant impact responses. If repeated iterations still fail to identify energy-sensitive features, this may suggest limitations in the sensing system, in which case adjustments to the sensor type, configuration, or placement could be considered.

The third step begins with Exploratory Data Analysis (EDA) to reveal structure and interdependencies in the dataset. Based on these insights, correlation analysis and Principal Component Analysis (PCA) are applied in parallel to reduce dimensionality and eliminate redundancy. Correlation analysis groups descriptors with strong dependencies, while PCA quantifies the contribution of each feature to overall variability, providing importance scores that guide ranking and selection.

To establish an input space that also reflects practical conditions, robustness is tested by adding Gaussian noise to simulate low-quality signals. The influence of noise is quantified through the Root Mean Square Error (RMSE) between original and perturbed values, expressed as a robustness score. This score is then combined with the PCA importance score to yield a selection score that balances relevance with consistency under uncertainties in measurements. Within each correlation cluster, only the feature with the highest selection score is retained, resulting in a final set of physics-based energy indicators $x^{(*)}$ that are relevant, independent, and reliable under noisy conditions. If no features meet these criteria, the process returns to the extraction stage for refinement based on updated domain knowledge.

In the final step, the identified physics-based energy indicators are utilised to train an Artificial Neural Network (ANN) for estimating impact energy. Once trained, the ANN employs inputs from the test dataset to generate predictions. Predictive performance is assessed under sparse and unbalanced conditions by comparing estimated values against experimental ground truth. This validation reflects conditions typically encountered in real-world applications.

The following sections provide a detailed description of each stage of the proposed framework, with an emphasis on integrating PIML principles into impact identification analysis. Particular attention is given to the treatment of observational bias from sensor-based measurements and its role in shaping a reliable input space. The framework does not rely on impact-specific processing steps, which makes it applicable beyond this case study. Consequently, it provides a transferable methodology for feature selection in other structural dynamics applications.

3.1. Feature extraction

The candidate features denoted as $x^{(0)}$ in Step I of Figure 1 form a multi-domain set of physics-motivated descriptors extracted from sensor signals during drop-weight impact tests. The complete list of candidate features is shown in Table 1, which compiles descriptors reported in prior studies as effective for characterising structural dynamics from time-series measurements. Their inclusion in the present framework is motivated by criteria specific to impact loading: features that can correlate with impact severity, capture the transient and localised nature of impact events, reflect the material behaviour, and remain measurable with practical sensor layouts.

The reason for grouping features into time, frequency, and time–frequency domains is that each captures a distinct but complementary aspect of the structural response. Time-domain descriptors quantify impact intensity and energy dissipation, linking directly to the overall energy content [83, 17, 19]. Frequency-domain features characterise the spectral distribution and identify dominant frequency components of impact events, reflecting the dynamic behaviour of the target structure [46, 67]. Time-frequency features capture energy distribution across multiple frequency bands, integrating both transient high-frequency components and low-frequency structural responses [69, 24]. The integration of these three perspectives yields a complete characterisation of the event, overcoming the limitations of single-domain approaches and increasing sensitivity to both global and localised effects.

This multi-domain perspective aligns with the principles of Physics-Informed Machine Learning (PIML). Embedding physical knowledge at the feature level introduces informative priors and supports generalisation under sparse and noisy conditions [29, 44]. In the next stage of the framework, the extracted descriptors are subjected to a parametric evaluation process, where relevance, robustness, and independence are assessed to construct an optimised input space.

3.2. Feature evaluation

The feature evaluation stage investigates whether candidate features exhibit statistically significant sensitivity to variations in impact energy. Impactor mass, impactor diameter, and impact location directly influence the amount and distribution of transferred energy [51, 88, 52], so these factors were included together with energy as the main parameters controlling the impact response. An F-test within an Analysis of Variance (ANOVA) framework was applied to quantify feature sensitivity while accounting for variations introduced by these parameters. The parameters and their levels were:

- i **Impact Energy:** Two levels (2 J, 20 J) to represent distinct loading conditions;
- ii **Impactor Diameter:** Two levels (16 mm, 50 mm) to assess variations in stress distribution and contact area;
- iii **Impactor Mass:** Two levels (0.5 kg, 2 kg) to account for differences in momentum transfer;

Table 1
Candidate features.

Domain	ID	Feature	Ref.	Description
Time	PA	Peak amplitude	[25]	Maximum signal amplitude
	TE	Transmitted energy	[83]	Area under signal envelope
	RT	Rise time	[21]	Time from signal onset to peak amplitude
	CTP	Counts to peak	[47]	Number of counts from onset to peak amplitude
	RA	Rise angle	[84]	PA / RT
	RMS	RMS	[39]	Root mean square
	EPR	Energy peak ratio	[26]	TE / PA
	NDA	Non-dimensional amplitude	[84]	PA / mean signal amplitude
	CF	Centroid frequency	[81]	PSD centre of gravity
	PF	Peak frequency	[47]	Frequency with maximum power
Frequency	WPF	Weighted peak frequency	[3]	$\sqrt{PF \cdot CF}$
	PCR	Peak centroid ratio	[65]	PF / CF
	RON	Roll-on frequency	[26]	Frequency at which 10% of total PSD has accumulated
	ROFF	Roll-off frequency	[26]	Frequency at which 90% of total PSD has accumulated
	AM	Approximation max	[69, 24]	Maximum value of low-frequency WPT component (level 3)
	DM	Detailed max	[69, 24]	Maximum value of high-frequency WPT component (level 3)
	AME	Approximation max energy	[69, 24]	Energy of AM component
	DME	Detailed max energy	[69, 24]	Energy of DM component
Time-Frequency				

PSD: Power Spectrum Density

WPT: Wavelet Packet Transform

iv **Impact Location:** Two positions (IC2 and IC4, Figure 3) to assess structural variations and attenuation effects.

The selected factors and their two-factor interactions were incorporated into a linear regression model to predict the response variable (i.e., candidate features), following the approach of Montgomery [64]:

$$y_n = \beta_0 + \sum_{i=1}^p \beta_i x_i + \sum_{i=1}^{p-1} \sum_{j=i+1}^p \beta_{ij} x_i x_j + \epsilon_n, \quad (1)$$

where x_i and x_j are the coded numeric values representing the four primary factors: impact energy, impactor diameter, impactor mass, and impact location. The parameter β_0 indicates the average response across all test runs. The coefficients β_i quantify individual factor effects, while β_{ij} measures the combined influence of two factors. Additionally, the term ϵ_n denotes a random error modelled as a normal distribution with a zero mean.

The statistical model described in Equation (1) allows for an analysis of variance to test the null hypothesis that either $\beta_i = 0$ or $\beta_{ij} = 0$. The test statistic is based on the expected values of the mean square error (ϵ_{MSE}) and the mean square regression (σ_{MSR}). In ANOVA, this measure is represented by the F-score as

$$F_{calc} = \frac{\epsilon_{MSE}}{\sigma_{MSR}}, \quad (2)$$

where ϵ_{MSE} and σ_{MSR} are defined as

$$\epsilon_{MSE} = \frac{\sigma_b^2}{b} \quad \text{and} \quad \sigma_{MSR} = \frac{\sigma_w^2}{w}. \quad (3)$$

In this formulation, the term σ_b^2 represents the variance in feature values between experimental conditions (e.g., energy, mass, diameter, and location), reflecting the influence of structural and loading parameters. In contrast, σ_w^2 represents

Table 2

Test matrix for confirmation experiments.

ID	Energy [J]	Diameter [mm]	Mass [kg]	Location
1	2	16	0.5	IC4
2	20	50	0.5	IC4
3	2	50	2	IC4
4	20	16	2	IC4
5	2	50	0.5	IC2
6	20	16	0.5	IC2
7	2	16	2	IC2
8	20	50	2	IC2

the variance within each setting, based on repeated measurements, and accounts for measurement noise or uncontrolled disturbances. The parameters b and w correspond to the number of independent comparisons between test conditions (between-group) and repetitions (error or within-group), respectively.

Finally, the significance of the means [23], defined here as the feature sensitivity to varying energy levels, was determined by comparing the computed F-score (F_{calc}) with the critical F-value (F_{crit}), obtained from F-distribution tables at a 5% significance level. A factor or interaction is considered statistically significant if the F-score exceeds the critical value.

This study used an orthogonal array [33] to structure the factor levels with statistical rigour and to represent impact conditions by systematically varying the four factors. The resulting design, represented by the test matrix in Table 2, was then used to define the confirmation experiments. These confirmation experiments were implemented as simulated impact responses generated according to this design. Synthetic data was required because the experimental dataset did not provide the necessary structured variation, while the validated simulation model was well-suited for this purpose. Details of the system configuration and numerical dataset are provided later in Section 4.

To assess variance significance, the eight confirmation experiments (ID1 to ID8 in Table 2) were arranged into ANOVA evaluations for the F-test. Table 3 details these evaluations, which focus on the effect of impact energy and examine whether impactor mass, diameter, and location also contribute or interact with energy in shaping the response. For example, ANOVA evaluation #1 evaluates impact energy at two levels (2 J, 20 J) and impactor diameter at two levels (16 mm and 50 mm), including their interaction, with two repetitions (n_1 and n_2). In the case of synthetic data, these repetitions arise from repeated factor combinations within the orthogonal array, allowing for balanced sampling and valid statistical comparisons. Overall, this methodology ensures that feature sensitivity to impact energy is evaluated under varying conditions relevant to operational scenarios.

3.3. Feature ranking and selection

Following feature evaluation, the feature ranking and selection scheme defines an optimised input space by eliminating redundancies and enhancing interpretability. This process integrates correlation evaluation, Principal Component Analysis (PCA), and robustness test to retain informative, independent, and stable features.

First, a correlation analysis is conducted to identify and eliminate redundant features. This analysis is essential as redundant features can obscure significant patterns in the data [10]. Linear dependencies between indicator pairs were assessed using the Pearson correlation coefficient, with values ranging from -1 to +1. A coefficient of -1 means perfect negative correlation, +1 perfect positive correlation, and zero represents no linear relationship between the variables [75]. For two random variables, S and Q , with k observations, the coefficient is defined as [28]

$$\rho(S, Q) = \frac{\sum_{i=1}^k (S_i - \bar{S})(Q_i - \bar{Q})}{\sqrt{\sum_{i=1}^k (S_i - \bar{S})^2} \sqrt{\sum_{i=1}^k (Q_i - \bar{Q})^2}}, \quad (4)$$

where $\bar{S}$ and $\bar{Q}$ denote the mean values of S and Q , respectively. To complement the feature ranking and selection step, a PCA is employed to identify features that account for the highest variance in the dataset [6, 38, 42, 54, 61, 75]. The

Table 3

F-test ANOVA evaluations based on combinations from confirmation experiments (ID1 to ID8).

ANOVA evaluation #	Factor		n_1	n_2
1	Diameter [mm]	Energy [J]		
	16	2	ID1	ID7
	16	20	ID4	ID6
	50	2	ID3	ID5
2	50	20	ID2	ID8
	Mass [kg]	Energy [J]		
	0.5	2	ID1	ID5
	0.5	20	ID2	ID6
3	2	2	ID3	ID7
	2	20	ID4	ID8
	Location	Energy [J]		
	IC4	2	ID1	ID3
	IC4	20	ID2	ID4
	IC2	2	ID5	ID7
	IC2	20	ID6	ID8

process involves determining the eigenvalues and eigenvectors of the covariance matrix to project the original dataset onto orthogonal Principal Component (PC) subspaces. Each PC is a normalised eigenvector that represents a direction of maximum variance.

Here, the energy indicators, referred to as $x^{(l)}$, are the input for PCA. They are organised into the structure of a feature matrix as follows:

$$\mathbf{x}^{(1)} = \begin{bmatrix} \overline{x_1} \\ \vdots \\ \overline{x_m} \end{bmatrix}^T = \begin{bmatrix} x_{1,1} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots \\ x_{k,1} & \cdots & x_{i,m} \end{bmatrix}, \quad (5)$$

with m representing the number of energy indicators and k denoting the number of observations. Accordingly, the PCA transformation is expressed in its general form as [61, 57]

$$\mathbf{x}^{(1)} = \mathbf{TP}^T, \quad (6)$$

where $\mathbf{P}$ is the loading matrix and $\mathbf{T}$ is the score matrix. In this context, the loadings represent the coefficients that indicate the degree to which each energy indicator contributes to a principal component. The scores represent the transformed values of the observations, indicating their position in a reduced feature space where a smaller set of principal components captures the main patterns of the original energy indicators. The first principal component captures the largest variance in the energy indicators, while subsequent components account for the remaining variance in decreasing order of magnitude.

To quantify the influence of each feature in the estimation process, an importance score $w^{(m)}$ was calculated for every indicator m . This score is defined as the sum of principal component loadings $p_i^{(m)}$ and scores $t_i^{(m)}$ across the total number of components N_c :

$$w^{(m)} = \sum_{i=1}^{N_c} t_i^{(m)} p_i^{(m)}. \quad (7)$$

While correlation analysis and PCA effectively assess feature relevance [10], real-world sensor data often contains noise, requiring robustness tests to ensure accurate signal representation. To address this, white Gaussian noise was added at an intensity of 5%, following Ghajari et al. [25]. The goal is to identify robust features within an informative and independent subset of descriptors, even in noisy conditions.

The influence of noise on each candidate feature was quantified using a robustness score $r^{(m)}$ based on the Root-Mean-Square Error (RMSE):

$$r^{(m)} = 1 - \epsilon_{\text{RMSE}} \quad \text{and} \quad \epsilon_{\text{RMSE}} = \sqrt{\frac{1}{k} \sum_{i=1}^k (y_i - \hat{y}_i)^2}, \quad (8)$$

where k represents the number of observations, y is the original data, and $\hat{y}$ is the noisy data. Lower RMSE values indicate higher robustness, resulting in higher scores.

To guide feature selection, the robustness score $r^{(m)}$ is combined with the PCA importance score $w^{(m)}$, defining the selection score $s^{(m)}$:

$$s^{(m)} = w^{(m)} r^{(m)}. \quad (9)$$

This composite score introduces a unified criterion for ranking features. It ensures that the retained descriptors are relevant, reliable under uncertainties in measurement, and independent by keeping only the strongest representative in each correlation cluster.

3.4. Input space validation

This work employs a machine learning strategy to validate whether the physics-based energy indicators enable accurate prediction of impact energy, particularly under limited data conditions. Beyond predictive accuracy, the aim is to examine how models behave when different amounts of domain knowledge are built into the input space. To this end, four configurations are compared: the proposed physics-based energy indicators and three reference strategies commonly employed in time-series prediction. These references are an independent feature model that applies correlation analysis, a candidate feature model that retains all extracted descriptors, and a CNN model that learns features directly from processed signals. A high-level overview of the four models is shown in Figure 2.

The models are ordered by decreasing reliance on domain knowledge. The proposed physics-based energy indicators model (Model 1, Figure 2a) incorporates the highest level of knowledge through targeted feature engineering based on statistical and physical criteria. The independent feature model (Model 2, Figure 2b) reduces this knowledge by skipping targeted ranking and selection, retaining only a correlation filter to remove redundancy; such filtering is well established in data science for mitigating overfitting [65, 18, 27]. The candidate feature model (Model 3, Figure 2c) further relaxes prior knowledge by retaining the complete set of extracted descriptors without any filtering or refinement, reflecting approaches commonly adopted in structural diagnostics [46, 69].

At the lowest level of embedded knowledge, the CNN model (Model 4, Figure 2d) represents a purely data-driven baseline. Here, convolutional layers learn feature maps directly from segmented time-series signals, with no manual feature design. This end-to-end approach is widely adopted in SHM for tasks that rely on automatic feature discovery [50, 83, 1]. Taken together, this comparative analysis assesses whether embedding domain knowledge yields measurable benefits in prediction performance under constrained data conditions.

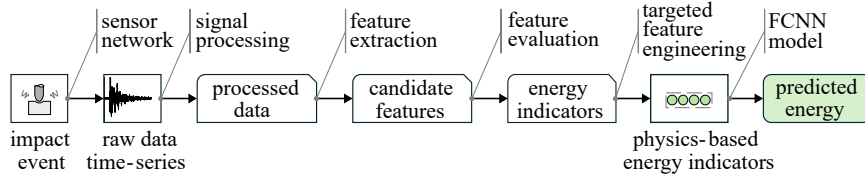
4. Datasets

To validate the proposed input space selection method, both synthetic and experimental datasets were generated from intermediate mass impact tests [68]. All datasets share the same structural configuration: a square composite panel with nominal dimensions of 1000 mm × 1000 mm × 3.55 mm. Figure 3 illustrates the impact test setup, and Table 4 lists the sensors and impact location coordinates.

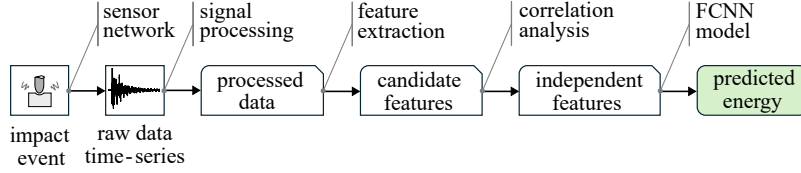
The numerical dataset was used exclusively for feature evaluation and sensitivity analysis under controlled, noise-free conditions, as described previously in Section 3.2. It was derived from an explicit finite element model validated against experimental findings in Bezes et al. [8]. The simulations replicate the panel geometry, boundary conditions, and material properties while spanning a representative range of impact energies and locations. This dataset corresponds to the confirmation experiments introduced in Table 2 for the ANOVA evaluations. Each simulated waveform was stored as a time series, and the statistical values are summarised in Table 5a.

The experimental dataset was used for feature ranking and selection (Section 3.3) and model validation (Section 3.4). A total of 66 waveforms were acquired from impact tests conducted in accordance with ASTM D7136M-15 [5], covering impact energies ranging from 3.81 J to 85.37 J across both pristine and damaged states. Impacts were

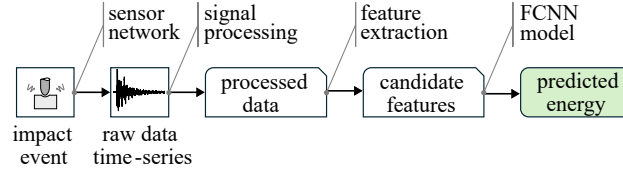
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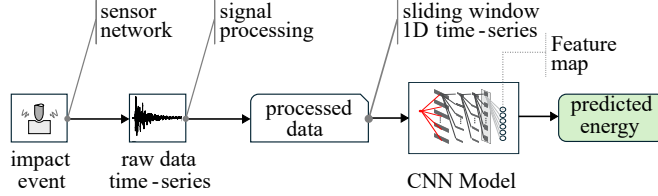
(a) Model 1: Physics-based energy indicators. Descriptors are filtered, ranked, and selected before FCNN estimation.



(b) Model 2: Independent features. Correlation analysis removes redundancy before FCNN estimation.



(c) Model 3: Candidate features. All extracted descriptors are input directly to the FCNN.



(d) Model 4: CNN. Convolutional layers learn feature maps directly from processed signals.

Figure 2: High-level overview of the four alternative model architectures considered for impact energy estimation.

applied at multiple panel locations (IC1-IC6 in Figure 3), using three different impactor diameters (16 mm, 25 mm, and 50 mm) and three impactor masses (0.776 kg, 1.154 kg, and 2.356 kg). The signals were recorded using a six-channel surface-mounted piezoelectric sensor network and stored as univariate time series. Further details regarding the material system, instrumentation, and acquisition procedures are provided in Marinho et al. [60].

To further test robustness, additional variability was introduced by adding 5% Gaussian noise to the experimental signals. This augmentation simulates harsher acquisition conditions while retaining the original measurements, resulting in a total of 132 samples for model development. Both the original and noise-augmented experimental signals were used in the analysis. Summary of statistics of impact energies is provided in Table 5b. The dataset is intentionally unbalanced, sparse, and limited in scope to reflect realistic constraints in SHM applications. Notably, the median impact energy (7.94 J) is substantially lower than the maximum recorded value (85.37 J), indicating a skewed distribution with a greater density of low-energy events.

5. Results and discussion

The results obtained from the proposed methodology for developing and validating an optimised input space for estimating impact energy are presented herein. The multi-domain candidate features are tested in sequence for four key properties: energy sensitivity, linear independence, relevance, and robustness under noise.

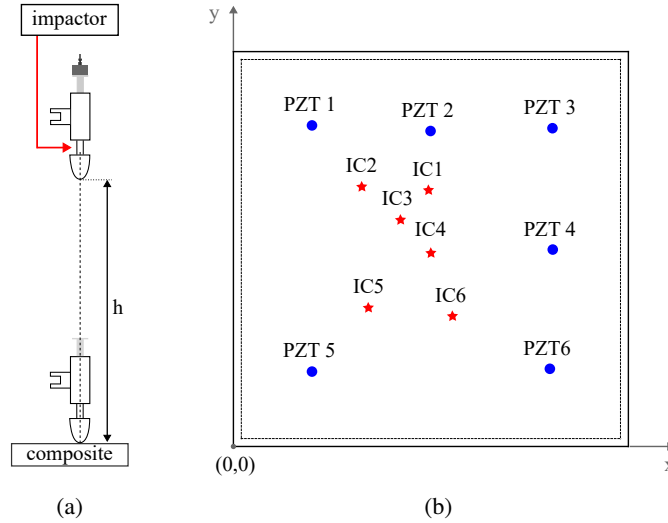


Figure 3: Schematic impact test configuration; • piezoelectric sensors (PZT) and ★ Impact Locations (IC): (a) drop-tower assembly with impact height (h) set by impact energy; (b) square composite panel ($1000 \times 1000 \times 3.55$ mm). Adapted from [60].

Table 4

Impact locations and sensor network coordinates.

ID	Coordinates [mm]	
	x	y
PZT1	188	786
PZT2	478	780
PZT3	779	781
PZT4	779	481
PZT5	188	172
PZT6	768	174
IC1	477	600
IC2	328	629
IC3	402	555
IC4	479	480
IC5	349	348
IC6	574	282

5.1. Feature evaluation

Feature evaluation was used to identify which candidate features, defined in Section 3.1, respond significantly to variations in impact energy. To this end, an F-test was applied as the statistical test of the null hypothesis. The null hypothesis H_0 states that the mean values of a feature remain equal across all impact energy levels, meaning the feature is not sensitive to energy variation. Rejecting H_0 ($H_0 = \text{False}$) shows that at least one group mean differs, and the feature is therefore classified as energy-sensitive. The results of this evaluation are presented in Table 6, where energy-sensitive features are highlighted in bold text.

In the time domain, Root Mean Square (RMS), Peak Amplitude (PA), Transmitted Energy (TE), Energy Peak Ratio (EPR), and Rise Angle (RA) showed strong sensitivity to impact energy. These parameters are intrinsically linked to signal amplitude and energy content, which consistently scale with impact energy. Specifically, RMS and PA quantify signal power and maximum amplitude, respectively, while TE provides a measure of total transmitted energy. EPR and RA capture transient signal characteristics, including rise time and energy distribution, which vary with impact severity [39, 25, 83, 26].

Table 5

Impact energy statistics.

(a) Numerical dataset.		(b) Experimental dataset.	
Number of samples	8	Number of samples	132
Number of unique targets	2	Number of unique targets	66
Minimum energy [J]	2.00	Minimum energy [J]	3.81
Maximum energy [J]	20.00	Maximum energy [J]	85.37
Mean energy [J]	11.00	Mean energy [J]	23.54
Median energy [J]	11.00	Median energy [J]	7.94
Standard deviation [J]	9.49	Standard deviation [J]	20.26

Table 6Feature evaluation with $F_{crit} = 7.7$.

Domain	ID	F_{calc}	H_0	Energy-sensitive?
Time	RMS	43.2	False	Yes
	TE	16.6	False	Yes
	PA	51.2	False	Yes
	EPR	32.7	False	Yes
	RA	30.6	False	Yes
	CTP	7.0	True	No
	RT	2.2	True	No
	NDA	1.8	True	No
Frequency	PCR	354.2	False	Yes
	ROFF	0.9	True	No
	CF	1.3	True	No
	WPF	9.0	False	Yes
	PF	9.0	False	Yes
	RON	1.0	True	No
Time-Frequency	AME	17.2	False	Yes
	AM	62.6	False	Yes
	DM	11.0	False	Yes
	DME	3.6	True	No

In the frequency domain, Peak Centroid Ratio (PCR), Peak Frequency (PF), and Weighted Peak Frequency (WPF) responded to spectral shifts induced by varying impact energy: higher energy produced shorter impacts and broader spectra, while lower energy produced longer impacts and lower-frequency spectra. Mechanical models confirm that impact duration and energy level govern the force profile and spectral content [85]. These shifts reflect modal participation and redistribution of vibrational energy consistent with frequency-dependent structural behaviour [80, 60, 59].

Among the time–frequency features, AM, AME, and DM were sensitive to impact energy, capturing propagation and attenuation mechanisms critical to energy partitioning [69, 24]. AM and AME are associated with low-frequency stress wave propagation and scale with energy input, whereas DM captures abrupt high-frequency changes, reflecting localised phenomena such as impact events [58].

In contrast, several features showed limited sensitivity to impact energy due to their underlying definitions and dependencies. Non-Dimensional Amplitude (NDA) cancels amplitude effects by normalisation, while Detailed Max Energy (DME) is dominated by stochastic high-frequency content such as noise and scattering, weakening its link to input energy [73, 69, 26]. Counts to Peak (CTP) and Rise Time (RT) depend on wave speed and geometry, which are independent of energy level [22]. Centroid Frequency (CF) and Roll-OFF/ON frequencies (ROFF, RON) describe relative spectral distribution rather than absolute amplitude, thus reflecting structural characteristics rather than impact energy [22].

In summary, the results confirm theoretical expectations from structural dynamics: features sensitive to amplitude and transient signal behaviour serve as effective indicators of impact energy [56, 62, 76]. The F-test thus ensures that only statistically relevant features are retained for subsequent stages of analysis. Based on the evaluation presented in Table 6, the selected features for further analysis include RMS, TE, PA, EPR, RA, PCR, WPF, PF, AME, AM, and DM.

5.2. Feature ranking and selection

The feature ranking and selection are built upon the energy-sensitive features identified through ANOVA (see Section 5.1). To ensure consistent comparison, each feature was normalised using min-max scaling [70], preserving underlying trends and eliminating amplitude-dependent biases in ranking metrics.

As an initial step, Exploratory Data Analysis (EDA) was employed to assess whether features exhibit consistent and physically meaningful behaviour with respect to impact energy. Two properties guided this qualitative assessment: monotonicity and trendability. Monotonicity denotes the degree to which a feature changes in a single direction without reversals, while trendability denotes the consistency of this curve shape across different energy levels. Both properties are widely used to evaluate whether a feature provides a reliable measure of system response [53, 40]. The range plots in Figure 4 show the relationships between normalised features and impact energy, with medians marked and whiskers extending to the most extreme data points that fall within 1.5 times the interquartile range [66]. They capture both the spread of the data at each level and the shift of the central value, which are key to evaluating feature consistency. Features that demonstrate either monotonicity or trendability are highlighted in green, emphasising their underlying trends.

Amplitude-based descriptors, including Peak Amplitude (PA), Transmitted Energy (TE), Root Mean Square (RMS), Approximation Max (AM), and Approximation Max Energy (AME), demonstrate a consistent increase with impact energy. Initially, linear trends are observed at lower energy levels; however, as energy increases, non-linear growth becomes evident. This shift indicates potential geometric or material non-linearities, which may arise from wave–structure interactions or damage mechanisms, as also highlighted by Melis et al. [62]. These non-linear effects may not only cause features to saturate but can also lead to accelerated growth, deviating from proportional scaling with energy input. The Energy Peak Ratio (EPR) and Peak Centroid Ratio (PCR) increase similarly with impact energy and exhibit a clear trend, although EPR loses monotonicity at the highest levels, where saturation effects emerge. The rise angle (RA) shows an inverse yet monotonic relationship with impact energy, reflecting transient response dynamics and enhanced damping effects, as demonstrated in previous studies [4, 30].

In the frequency domain, the Peak Frequency (PF) and Weighted Peak Frequency (WPF) exhibit considerable scatter and irregular trends with respect to impact energy. Although sensitive to excitation changes, their consistency is affected by abrupt shifts in dominant modes and spectral redistribution across energy levels [48]. These factors introduce heteroscedasticity, reducing their suitability for stand-alone energy estimation. Despite these limitations, frequency-based features offer valuable supplementary insight into structural dynamics and enhance the overall characterisation of impact response.

Furthermore, the Detailed Max (DM) shows a piecewise linear pattern, increasing with energy up to about 45 J and then declining. Although this indicates a clear trend, the bi-linear behaviour lacks monotonicity because it reverses direction at higher levels. The absence of monotonicity may limit its suitability for energy estimation, as one DM value may correspond to different energy levels, creating ambiguity and lowering predictive accuracy. The decline at higher energies suggests a shift from elastic wave propagation to attenuation of high-frequency components, possibly driven by geometric non-linearities or the onset of damage. Literature supports this interpretation, reporting that structural defects scatter stress waves and dissipate vibrational energy into heat at elevated excitation levels [65, 24, 12].

To complement the univariate analysis, correlation analysis was performed to assess redundancy and complementarity among descriptors across signal domains. This step mitigates information overlap and supports input space disentanglement, which is essential for effective feature representations [74]. Groups in Table 7 are coded by domain and statistical similarity: T for time-domain features, F for frequency-domain features, and W for time–frequency (wavelet-based) features. Within each domain, the numbering (e.g., T1, T2) identifies correlated clusters derived from Pearson correlation coefficients (Equation (4)). These relationships are visualised in Figure 5, highlighting domain-specific associations. The additional columns in Table 7 are introduced here for completeness but will be explained in detail after the PCA and robustness analyses later in this section.

In the time-domain (Figure 5a), amplitude-based features (PA, TE, RMS) exhibit strong intercorrelation, driven by their shared sensitivity to signal magnitude and energy content. These descriptors form a coherent cluster,

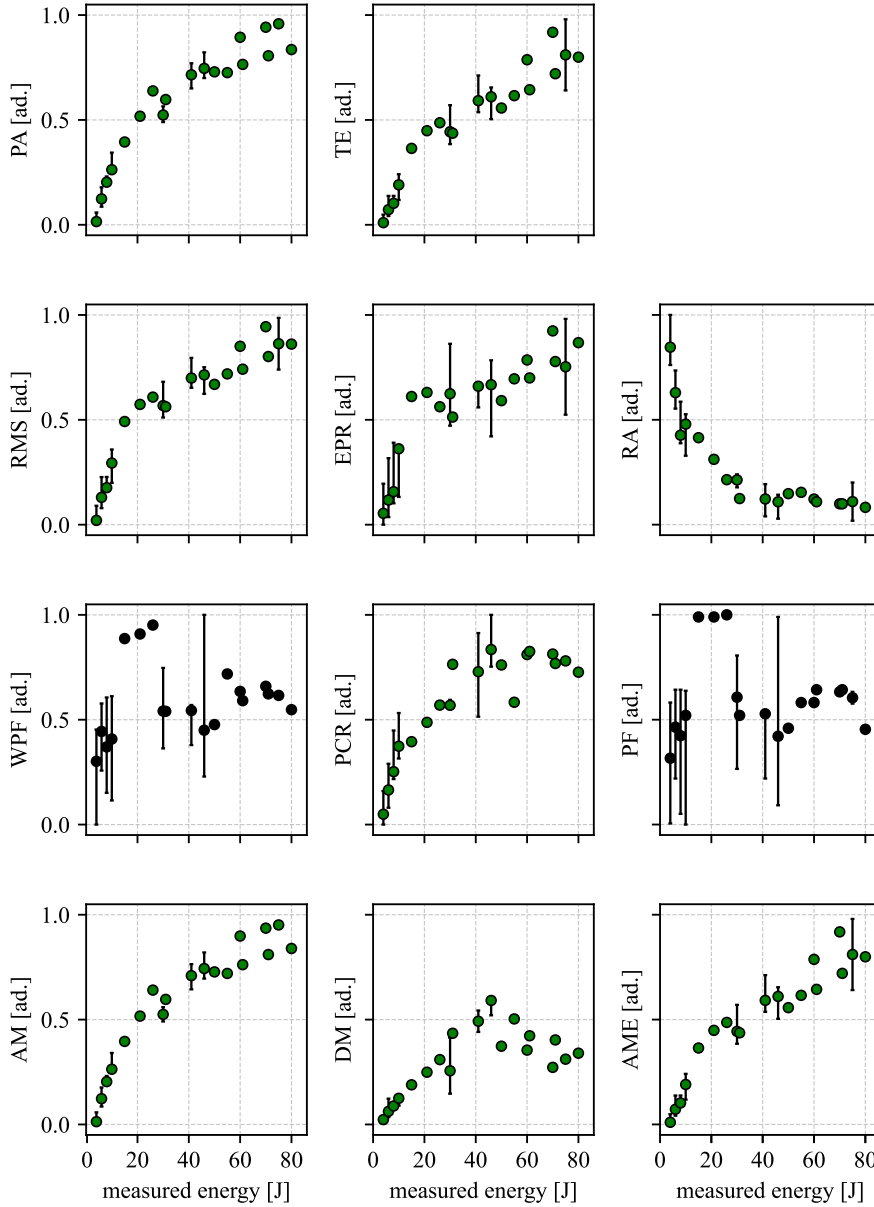


Figure 4: Univariate range plots of energy indicators for EDA. Features that exhibit either monotonicity or trendability are highlighted in green.

demonstrating predictable scaling with wave amplitude in the elastic regime. By contrast, RA exhibits a high negative correlation with these features, consistent with its inverse relationship with energy identified during EDA.

In the frequency-domain (Figure 5b), PF and WPF showed a strong correlation ($p = 0.95$), reflecting mutual sensitivity to dominant spectral content. However, PCR exhibited weak correlations with both PF ($p = 0.09$) and WPF ($p = 0.25$), suggesting that it represents spectral shape rather than frequency magnitude. This independence makes PCR complementary to PF and WPF, since together they provide distinct yet related information on modal behaviour, as also noted in studies on spectral clustering [2].

In the time-frequency domain (Figure 5c), AM and AME exhibit a near-perfect correlation ($p = 0.99$), reflecting shared sensitivity to low-frequency stress waves and energy distribution. DM shows a moderate correlation with both AM and AME ($p = 0.77$ and $p = 0.70$, respectively), indicating its complementary role in capturing high-frequency transients while maintaining sensitivity to energy variation.

Table 7

Feature ranking and selection at coupon level.

Domain	Group	ID	$w^{(m)}$	$r^{(m)}$	$s^{(m)}$	Rank	Evaluation
Time	T1	RMS	0.80	0.98	0.78	2	* / •
	T1	TE	0.80	0.97	0.77	3	* / •
	T1	PA	0.80	0.99	0.79	1	* / ••
	T2	EPR	0.76	0.95	0.73	1	** / ••
	T3	RA	0.76	0.92	0.70	1	** / ••
Frequency	F1	PCR	0.78	0.89	0.69	1	** / ••
	F2	WPF	0.60	0.91	0.55	1	** / ••
	F3	PF	0.45	0.93	0.42	1	** / ••
Time-Frequency	W1	AME	0.80	0.99	0.79	1	* / ••
	W1	AM	0.80	0.98	0.79	2	* / •
	W2	DM	0.72	0.63	0.46	1	** / ◇

Legend:**Scores:** $w^{(m)}$ importance score (Equation (7)); $r^{(m)}$ robustness score (Equation (8)); $s^{(m)}$ selection score (Equation (9)).**Evaluation:** ◇ not stable; * not independent; ** independent; • relevant; •• most relevant.**Rank:** Ranking per group based on selection score.

A Principal Component Analysis (PCA) was conducted in parallel with correlation analysis to evaluate the variance structure of the feature set. In accordance with previous literature [79], the number of retained components was defined to capture over 95 % of the total variance. As illustrated in Figure 6, the first five components collectively account for 98.95 % of the cumulative variance, with PC1 alone explaining 78.94 %.

The PCA-derived importance scores, summarised under the column $w^{(m)}$ (Equation (7)) in Table 7, confirm the trends identified in the exploratory and correlation analyses. RMS, TE, and PA, all from the time domain, each attained a score of 0.80, highlighting their dominant contribution to the variance structure. Their similar scores reflect the strong correlations observed earlier, illustrating how PCA assigns comparable importance to highly correlated features. EPR and RA both scored 0.76; in particular, the RA contribution reflects its distinct variance pattern, which aligns with its inverse relationship to impact energy, as also indicated by the negative correlation coefficients in Figure 5a.

In the frequency domain, PCR achieved the highest score (0.78), confirming its statistical independence from PF and WPF, as indicated by weak correlations. The lower scores of WPF (0.60) and PF (0.45) correspond to their irregular and dispersed trends observed in the exploratory analysis. In the time-frequency domain, AM and AME both achieved scores of 0.80, consistent with their near-perfect correlation. DM, with a moderate score of 0.72, complements this pair by capturing additional high-frequency dynamics not fully represented by AM or AME.

A robustness assessment complemented the feature ranking and selection step through a noise sensitivity analysis, in which 5% Gaussian noise was introduced to the dataset. Robustness scores $r^{(m)}$ (Equation (8)), reported in Table 7, quantified the resilience of each feature against these perturbations. Figure 7 illustrates the resultant effects, presenting median values for each energy level to elucidate underlying trends.

Amplitude-based features (PA, RMS, TE, AM, and AME) demonstrated high robustness ($r^{(m)} \geq 0.97$), maintaining consistent energy trends in the presence of noise. This robustness is consistent with their strong energy sensitivity and dominant contribution to variance. As previously confirmed by both exploratory and PCA analyses, these descriptors showed stable monotonic behaviour and high importance scores. Furthermore, since additive white Gaussian noise affects all dimensions uniformly in PCA [72], these high-importance features tend to preserve their relative relationships under perturbation. This robustness results from their signal variance substantially exceeding the noise level, whereas features with lower importance scores are more vulnerable to saturation and distortion effects [34, 35].

The remaining time domain features, EPR and RA, also exhibited high robustness ($r^{(m)} \geq 0.92$), confirming their reliability for impact identification tasks. In contrast, frequency-domain features demonstrated moderate robustness, with PCR, WPF, and PF achieving scores ranging from 0.89 to 0.93. Although these features maintained a sufficient level of robustness, they were more affected by noise and modal shifts compared to amplitude-based descriptors.

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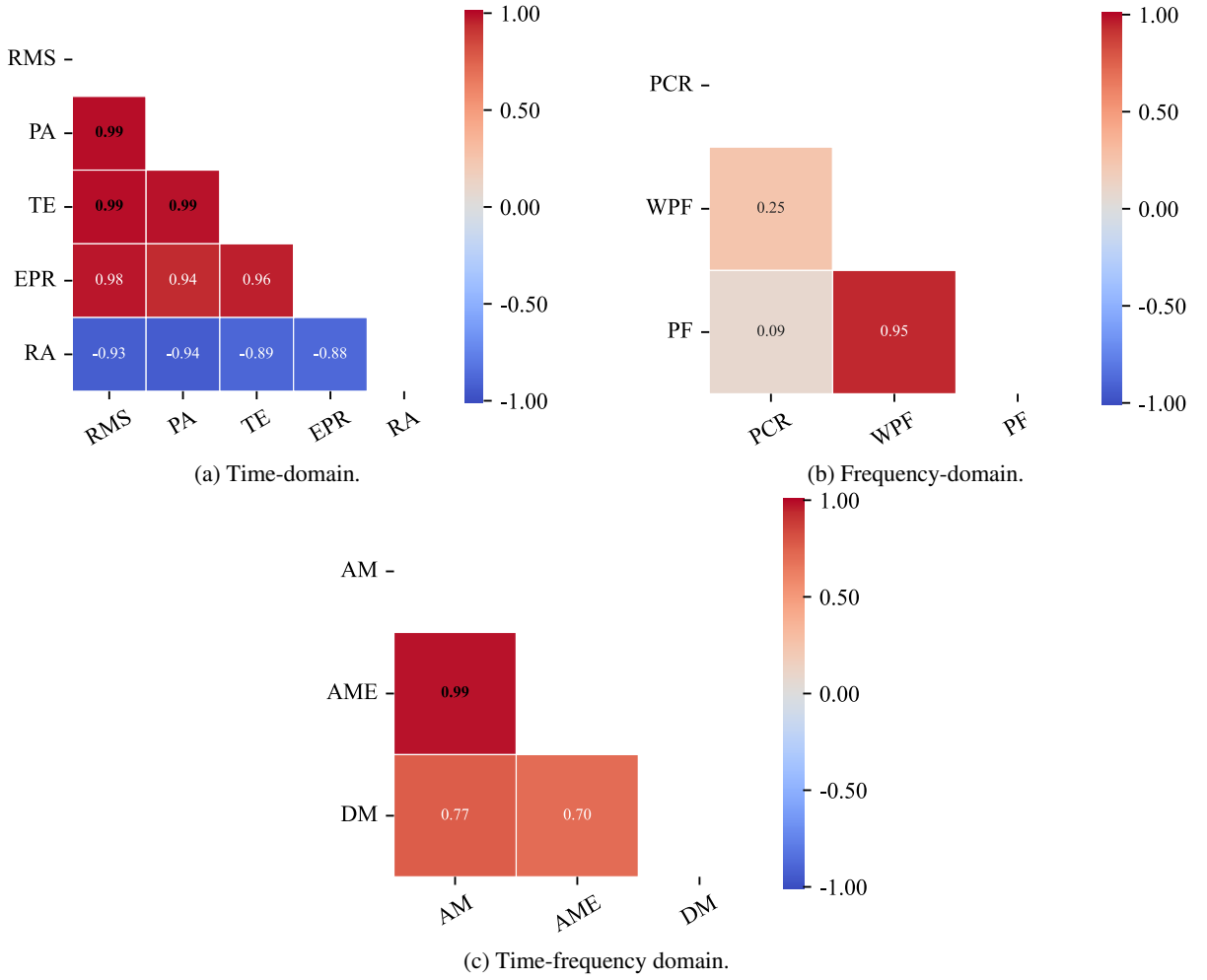


Figure 5: Correlation analysis results.

Within the time-frequency domain, DM was significantly more sensitive to noise ($r^{(m)} = 0.63$), as indicated by increased scatter under perturbation. This greater sensitivity arises because noise predominantly affects high-frequency components, which are captured by the detailed coefficients [7], limiting its applicability under realistic operating conditions.

The selection score $s^{(m)}$ (Equation (9)), comprising both importance and robustness scores, is summarised in Table 7 and directs the final evaluation of descriptors. This phase synthesises findings from correlation structure, PCA-based relevance, and noise sensitivity analysis. Rather than applying a strict cut-off, the framework guides informed feature selection. Appropriate descriptors strengthen confidence in the input space, while weaker ones expose its limitations and indicate where predictive accuracy may be improved. Finally, the selection score ranks stable descriptors of comparable importance within correlated clusters, enabling a consistent choice among redundant features.

In the time domain, all energy-sensitive features exhibited sufficient robustness. However, correlation analysis revealed redundancy among RMS, TE, and PA (group T1). PA was retained due to its highest selection score in this cluster. EPR and RA also demonstrated robustness and independence and were therefore included in the final feature set. In the frequency domain, PCR, WPF, and PF fulfilled the criteria for independence and robustness and were retained accordingly. Within the time-frequency domain, AM and AME displayed a strong correlation, with AME selected due to its slightly superior robustness. DM, although energy-sensitive, failed to meet the robustness criterion and was excluded from the final input layer.

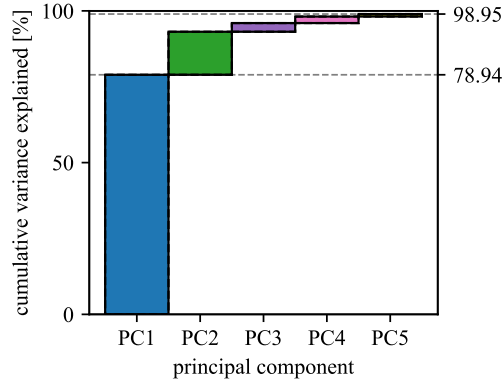


Figure 6: Explained variance of principal components.

In conclusion, feature selection was accomplished through a process of elimination, refining the input space to include only robust, independent, and energy-sensitive descriptors. The final set of physics-based features for impact energy estimation comprises PA, EPR, RA, PCR, WPF, PF, and AME. By integrating descriptors from the time, frequency, and time–frequency domains, the selection process ensures a complete picture of the impact event. This multi-domain perspective aligns with structural dynamics principles, embedding them directly into feature design and yielding a physics-informed input space for impact energy estimation.

5.3. Input space validation

The constructed input space, based on selected physics-based energy indicators, was validated for its effectiveness in predicting impact energy. Its performance was compared against three reference methodologies, as outlined in Section 3.4. For clarity, the input space of each model is summarised below:

- **Model 1** (Physics-based energy indicators): PA, EPR, RA, PCR, WPF, PF, and AME, as defined by the proposed feature selection process;
- **Model 2** (Independent features): PA, RT, CTP, RA, EPR, NDA, CF, PF, WPF, PCR, RON, ROFF, DM, and DME, obtained from Pearson correlation analysis of the full candidate set without distinguishing domains;
- **Model 3** (Candidate features): all descriptors listed in Table 1;
- **Model 4** (CNN): abstract feature representations through convolutional operations.

All models were trained on identical data partitions to ensure a fair comparison. The dataset was split into training (80%), validation (10%), and test (10%) subsets and included both original measurements and augmented data. Model implementation details, architectures, and hyperparameters are provided in the following subsections.

5.3.1. FCNN implementation

Artificial Neural Networks (ANNs) were employed for energy predictions using the input spaces of Models 1, 2, and 3. Fully Connected Neural Networks (FCNNs) were selected for their effectiveness in capturing non-linear relationships between signal-derived features and impact energy through iterative optimisation [9, 31, 25].

The overall workflow is illustrated in Figure 8 and consists of four main steps. First, raw data $\mathbf{D}^*$ were pre-processed using the signal processing framework described in Marinho et al. [60]. Second, candidate features were extracted as outlined in Section 3. Third, the input space was defined, with the input vector differing across models. Fourth, the FCNN used Tanh activation functions [78] to establish non-linear mappings between the input features and the target impact energy. Training minimised the Mean Squared Error (MSE) between the network output $\mathbf{E}$ and the experimental ground truth $\mathbf{E}^{(*)}$, producing a set of optimised parameters Θ . Model performance was finally assessed on independent test data using standard error metrics.

The network settings were selected through a grid search over the hyperparameter space summarised in Table 8. In this process, three hyperparameters were varied in parallel: the fully connected layer size (n_h), the number of fully connected layers (L_h), and the learning rate (lr). Each configuration was tested with five-fold cross-validation, ensuring

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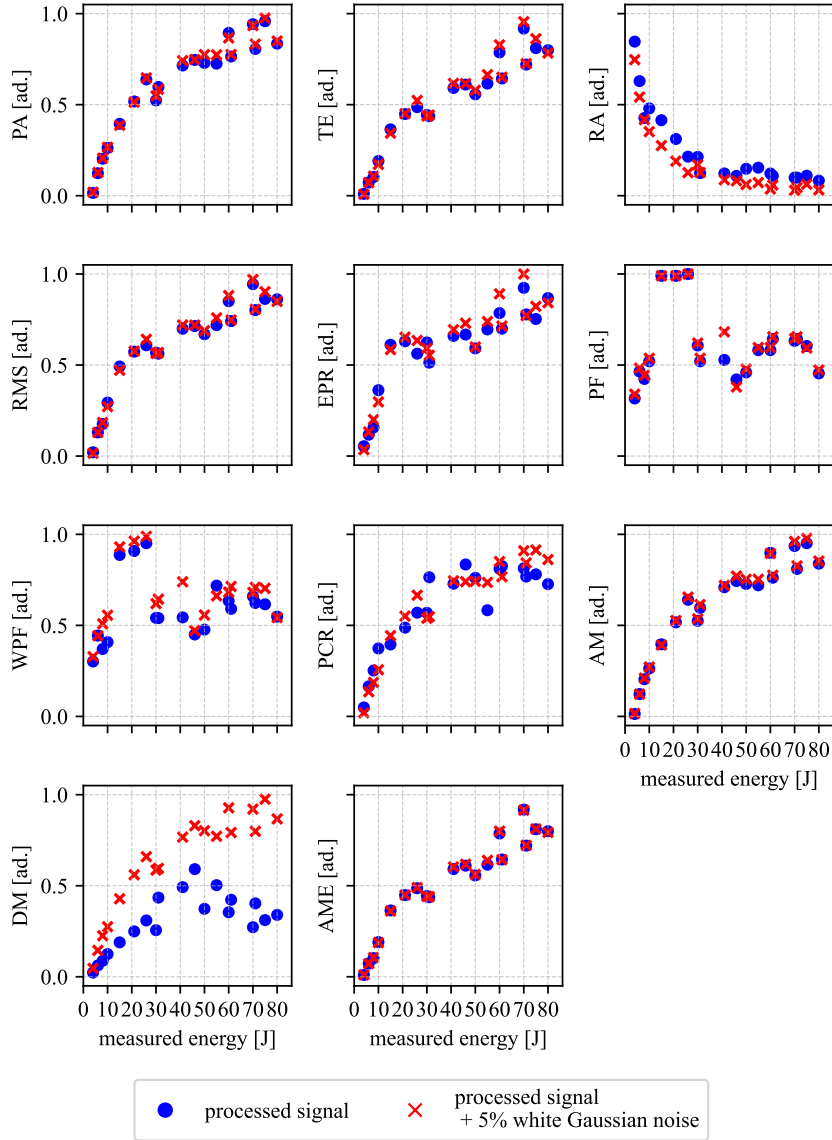


Figure 7: Robustness of features under added noise.

that the chosen parameters were generalised across the dataset [20]. For each fold, the dataset was partitioned into independent 80/20 train and test splits, and the mean coefficient of determination (R^2) across folds was used as the performance criterion.

The results of this procedure are shown in Figure 9, where the colour scale indicates the average R^2 obtained for each parameter combination. The grid search identified the best performance at $n_h = 32$, $L_h = 2$, and $lr = 1 \times 10^{-3}$. The selected configuration, together with all implementation details of the FCNN, is reported in Table 9. These settings were used in the residual and performance analyses.

5.3.2. CNN implementation

The CNN acts as a regression model for predicting impact energy. Unlike the previous models, which rely on explicit feature selection, the CNN learns feature maps directly from measured impact responses. The network architecture is shown in Figure 10. It has six input channels that process 1-D time-series measurements as overlapping time slices, generated with a sliding window of 1000 samples and a shift of 200 samples (80% overlap). The input layer is

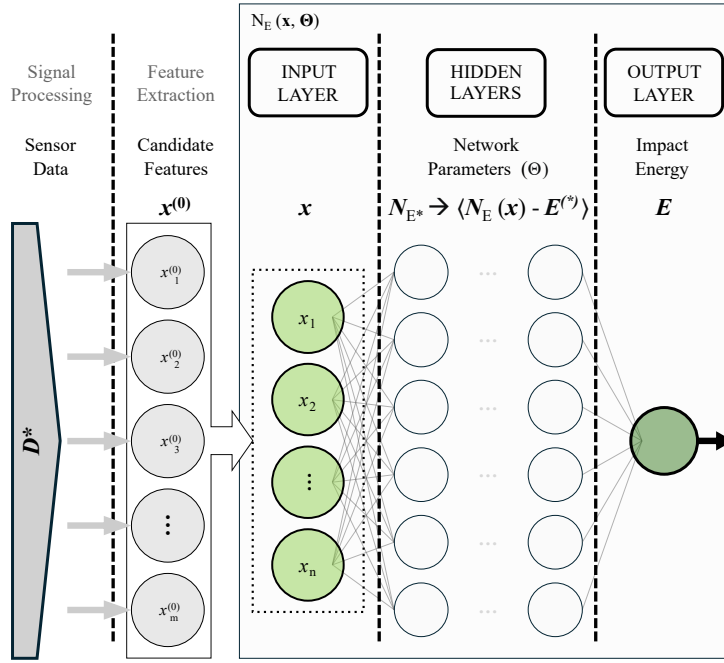
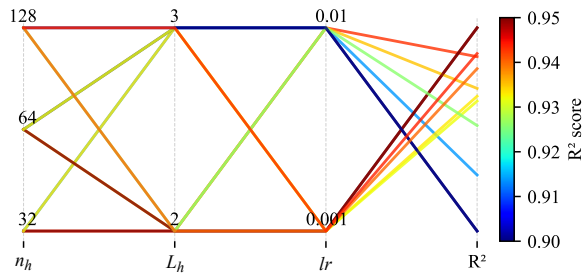


Figure 8: Schematic of the FCNN (Models 1–3).

Table 8

Hyperparameter search space for tuning the FCNN model (Models 1–3).

Category	Parameter	Values
Model architecture	fully connected layer size, n_h	32, 64, 128
	number of fully connected layers, L_h	2, 3
Training setup	learning rate, lr	0.01, 0.001

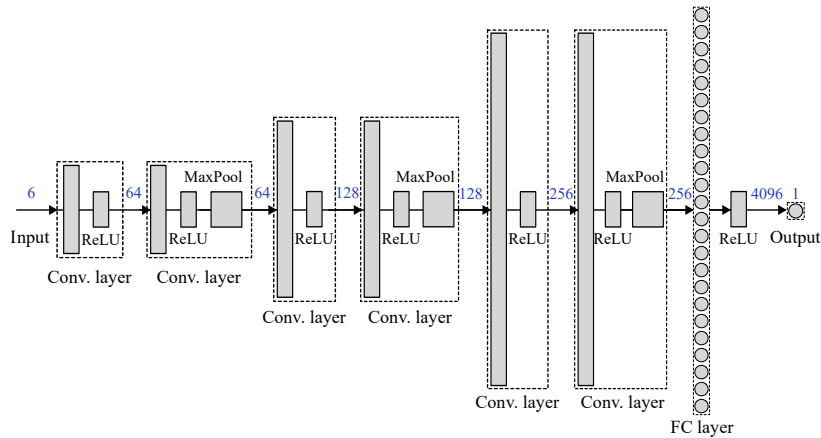

 Figure 9: Grid search with k -fold cross-validation results. (n_h : fully connected layer size; L_h : number of fully connected layers; and lr : learning rate).

followed by convolutional layers with 64, 128, and 256 channels, each combined with ReLU activation and periodic max-pooling. A fully connected layer produces a single output corresponding to the predicted impact energy. During training, the model with the lowest loss per iteration was saved for prediction. A patience threshold of 15 epochs is applied, meaning training stopped early if no further improvement was observed for 15 consecutive iterations. The corresponding hyperparameters and configuration choices are listed in Table 10. This configuration was obtained through a focused manual search to optimise windowing and training, which was sufficient for the scope of this study.

Table 9

Implementation details used for impact energy predictions using FCNN (Models 1–3).

Parameter	Value
Network architecture	
Architecture	Fully-Connected Neural Network
Fully connected layers, n_h	2
Fully connected layer size, L_h	32
Output layer dimension	1
Activation function	Tanh
Batch normalisation	True
Training procedure	
Optimizer	Adam
Criterion	MSELoss
Learning rate, lr	1×10^{-3}
Batch size	Full-batch
Max epochs	10000
Patience	1000

**Figure 10:** Architecture of the CNN used for impact energy estimation.

5.3.3. Predictive analytics

The predictive performance of the models was evaluated using the experimental dataset described in Section 4. The dataset shows an imbalanced distribution of impact energies, characterised by a higher concentration of samples at lower energy levels and fewer at higher levels. It is important to acknowledge that this uneven distribution can result in models that are better trained and more accurate in the low-energy range, but less reliable at high energies. As a result, average accuracy metrics may be slightly overestimated, as model performance in the majority (low-energy) region dominates the overall evaluation. However, this effect occurs similarly across all models and therefore does not affect the relative performance trends discussed below.

The comparative results are summarised in Figure 11, which visualises both residual patterns and prediction behaviour across input space configurations. CNN (Model 4) processes each measurement through multiple overlapping sliding windows, resulting in several predictions per sample. Accordingly, whiskers depict the full range of predictions across these windows and provide a measure of uncertainty, while red markers indicate the median predicted energy at each true energy level. Residuals for the CNN were computed using these median predictions, representing the central estimate across all window outputs for each impact test sample. In contrast, FCNN models (Models 1–3) produce a single prediction per sample, and therefore, no whiskers are shown. The bar plot in the same figure highlights the uneven distribution of impact energies.

Table 10

Implementation details used for impact energy predictions using CNN (Model 4).

Parameter	Value
Input configuration	
Input channels	6
Slice size	1000 samples
Slice shift	200 samples
Network architecture	
Architecture	Convolutional Neural Network
Convolutional layers	6
Convolutional layers size	64, 64, 128, 128, 256, 256
Kernel sizes	5, 5, 5, 5, 5, 5
Fully connected layers	1
Fully connected layer sizes	4096
Activation function	ReLU
Batch normalisation	True
Training procedure	
Optimizer	Adam
Criterion	MSELoss
Batch size	32
Initial learning rate	1×10^{-3}
Learning rate scheduler	step=10, gamma=0.1
Maximum epochs	60
Patience	15

Among the assessed methodologies, the physics-based FCNN showed the lowest Mean Absolute Percentage Error (MAPE) at $\epsilon_{x^{(*)}} = 5.23\%$. This approach outperformed the independent features model ($\epsilon_{ind} = 13.97\%$), the CNN ($\epsilon_{CNN} = 14.95\%$), and the FCNN trained on the complete candidate features set ($\epsilon_{x^{(0)}} = 16.48\%$).

This performance ranking is further supported by residual analysis. The physics-based energy indicator model shows residuals closely clustered around zero, demonstrating consistent accuracy across the entire energy range. In contrast, both alternative FCNN configurations exhibit higher residual values resulting from the incorporation of unrefined features. The latter limitation hinders the ability of the model to isolate relevant patterns, particularly under increased non-linearities and noise introduced during data augmentation. Although correlation-based feature selection (Model 2) mitigates redundancy and yields moderate improvements, it fails to ensure robustness or sensitivity to impact energy, ultimately reducing reliability.

The CNN exhibited a distinct prediction pattern: individual windows often produced inaccurate estimates, yet aggregating their outputs through median values yielded a reliable overall prediction. In this context, prediction noise across all window outputs increased in regions with limited training data, particularly above 10 J, where the whiskers in the scatter plot of Figure 11 broadened considerably, indicating greater variability among individual window predictions. In contrast, median outputs aligned well with the ground truth, as the median reduced the influence of outliers and provided a stable central estimate. Although the median results were fairly accurate, CNNs remain more complex to implement and tune than feature-based models. They also offer limited interpretability due to their black-box nature and therefore lack the transparency of feature-based approaches. Furthermore, while sliding-window strategies can improve numerical stability and efficiency, the fundamental trade-off between model complexity, computational cost, and data dependence remains a drawback in CNN-based modelling. This outcome aligns with previous findings that purely data-driven models, such as CNNs, rely heavily on large, well-conditioned datasets and exhibit reduced performance when those conditions are not met [41].

Taken together, the results highlight the advantage of physics-informed modelling with selective input design for impact energy estimation. By establishing a compact and physically meaningful input space, the physics-informed model achieves consistent performance across a challenging data regime that is affected by noise, sparsity, and non-linearity. This approach not only enhances predictive accuracy but also provides a robust framework for integrating

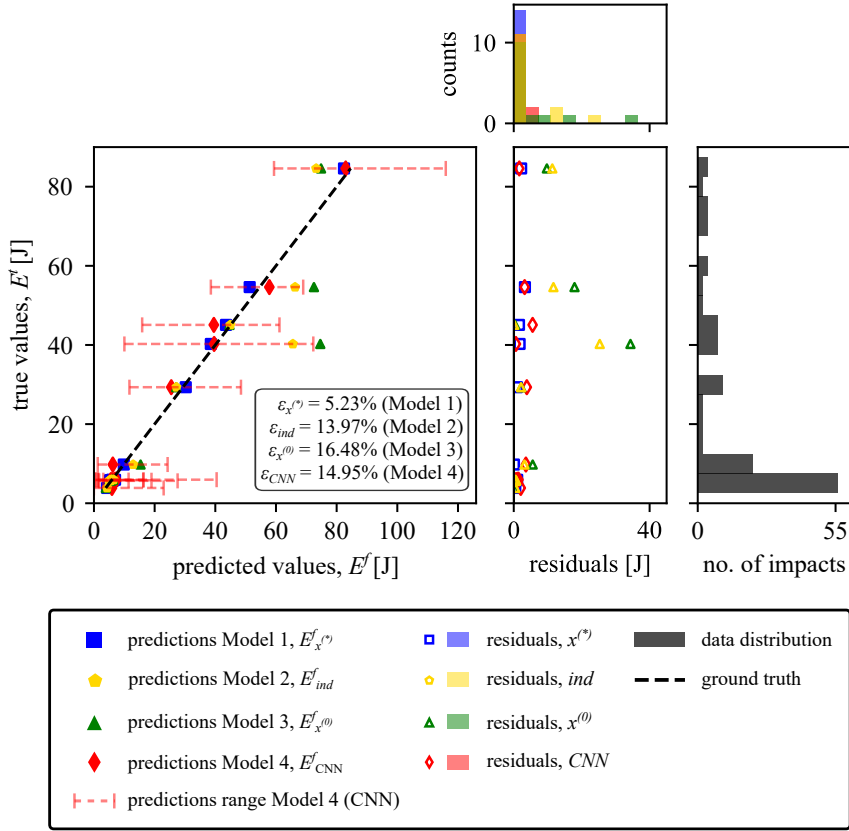


Figure 11: Comparison of impact energy predictions using physics-based energy indicators $x^{(*)}$, correlation-based features x^{ind} , and the full candidate set $x^{(0)}$ within a FCNN, and a black-box CNN.

structural dynamics principles into data-driven methodologies, paving the way for more effective and reliable impact energy assessments in structural health monitoring contexts.

6. Concluding remarks

The proposed framework demonstrates that embedding physics-informed principles into the feature design process enables more reliable impact energy estimation, particularly under measurement constraints and limited data availability. Its main contribution lies in combining observational bias with targeted feature selection, which reduces dependence on large training sets and delivers consistently better predictive accuracy than models trained on unstructured data or conventional signal metrics.

Physics-motivated descriptors are extracted from time, frequency, and time–frequency domains and evaluated using a targeted feature selection methodology. A quantitative ranking procedure based on composite scoring metrics balances physical relevance with statistical robustness, providing a practical tool to quantify descriptor performance, enable transparent comparison, and guide the retention of the most informative indicators. This process yields a compact and meaningful input space that preserves physical interpretability while supporting reliable energy estimation.

Grounded in structural dynamics, the framework captures critical dynamic mechanisms through selected multi-domain features, linking observed responses to trends that follow established principles in structural behaviour. This explicit physical motivation strengthens model transparency and builds confidence in energy predictions. In addition, the framework enhances explainability by revealing weak points in the input space: if predictive accuracy is low, the importance and robustness scores can indicate which features perform poorly and why, providing insight for further improvement.

Despite notable strengths and strong predictive performance, certain limitations must be acknowledged. The magnitude of measurement noise and additional structural non-linearities can influence the stability of predictions. Furthermore, reliance on expert judgement for feature definition may introduce subjectivity when establishing physical constraints or relevance thresholds, particularly in complex or poorly characterised systems.

To address these limitations, future work should extend the framework to more complex structural configurations and enhance model design by integrating additional sources of physics-based biases, including relevant governing equations or physical constraints. Incorporating further physical insight is also expected to enhance the extrapolation capability, enabling the methodology to perform reliably outside the original training domain. Another promising direction involves the use of multi-fidelity feature extraction, where features derived from simulation data can complement experimental observations, improving data efficiency in scenarios where testing is costly or unavailable. Together, these developments would improve generalisation and support scalability in impact energy estimation.

In summary, the proposed methodology provides a robust foundation for accurate, interpretable, and scalable models in impact estimation. The combination of physically informed feature design and statistical evaluation ensures robustness under practical data constraints, demonstrating strong potential for deployment in monitoring and maintenance workflows.

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