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Ensemble learning based sustainable approach to rebuilding metal structures prediction

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The effective implementation of the European Green Deal is based on closing cycles by means of reusing products and extending their durability, especially for steel products in the construction industry. The Life Cycle Assessment gives an opportunity to determine the potential impact caused on the environment by building structures and it is used mainly at the early design stage. At the same time, there are significant gaps when it comes to predicting properties of steel products at the last stage of the life cycle of existing buildings in the End of Life Stage (C1-C4) phases and especially D—Benefits and Loads Beyond the System Boundary. This paper uses machine learning (ML) in order to solve the problem of predicting the reusability of construction steel based on the determination of its yield strength by a non-destructive magnetic method. This will give an opportunity to make informed decisions when using this steel again. The research uses machine learning approaches that include regression problems. However, the use of ensemble learning significantly improves quality and accuracy of the results, while demonstrating its advantage in combining multiple models for obtaining more accurate predictions. The research results show that the WeightedEnsemble ensemble method (which includes 8 models) has the best prediction accuracy (MSE = 441 MPa and RMSE = 21 MPa). This method has high accuracy and low delay of conclusion (IL = 0.119 s) when predicting the tensile strength limit (MPa) based on the data of non-destructive testing of structural steel products. . The innovation of the development lies in the ability to provide an automated tool to support informed decision-making for the reuse of building steel for construction site professionals. The accuracy of the ensemble model and its potential for integration with existing practices indicate significant progress in managing steel reuse processes at the final stage of the building life cycle – stage D.

Keywords European Green Deal, Machine learning, Prediction, Metal structures, Sustainable approach

Active response to a number of negative global trends has triggered the rapid transition of the European Green Deal[1], an EU economic development programme and a set of policy initiatives adopted in 2019 aimed at transforming Europe into a climateneutral continent[2], improving the wellbeing of citizens, protecting biodiversity and greening the economy by 2050[3].

The trend of recent decades is the rapid increase in population to 9 billion in 2050, which will lead to a significant annual increase in demand for natural resources, with construction being the main consumer[4]. The construction sector plays a crucial role in the consumption of raw materials. As early as 30–40 years ago, the construction contribution to resource consumption was 40% of materials and a third of energy consumption

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worldwide[5]. Today, the construction sector consumes more than 60% of extracted raw materials and produces 40% of energy related CO_2emissions[6]and acid rain agents. On average, each EU citizen consumes approximately 4.8 tonnes of minerals for construction. At the same time, the environmental impact is caused by both mining and processing of construction materials, in particular through energy consumption—the industry accounts for 36% of electricity generated and related emissions. Therefore, the responsible use of resources, global climate change efforts and clean production, which are the goals of the European Green Deal[7,8], place the construction industry at the forefront of the sector's efforts (Fig. 1).

According to studies by E. Nolasco[9]and Yeheyis M[10]. construction waste in some countries reaches the level of 25–60%. According to the research of Kibert Ch[11]., waste is generated at all stages of the life cycle of buildings, but the largest and most influential phase in terms of the generation of construction and renovation waste is at the end of the life cycle, which accounts for 50% of the total amount of waste. This is due to the use of linear models as opposed to circular economy models[12]. According to circular economy models, materials that have served their time should be reused. Structural elements should be reused, and according to Hopkinson P[13]., Zabek M[14]. and Finamore M[15]., they are to act as material banks for new buildings, while storing components and materials in a closed loop, Marin J[16]., Cai G[17].. The difficulty of implementation is due to the fact that according to Fernanda G[18]. this kind of innovation takes much longer to implement, since buildings are mostly unique projects with a large supply chain, compared to industry.

Due to the constant rise in raw material prices, the construction industry is rapidly adopting innovative solutions[19,20], using efficient, environmentally friendly materials, reusing, recycling and extending the life of existing structures. However, the situation can only be changed dramatically if we move from the current linear consumption model to a more sustainable one[21,22], using a circular economy approach that incorporates cyclical material flows in production systems and ecoefficiency to ensure a more sustainable construction sector . According to the circular economy concept, the construction industry needs to close cycles by reusing waste and resources, slowing down material cycles by reusing products and extending their durability, especially for steel products[12,23].

As a building material, steel has its undeniable advantages. This material has one of the most favorable strength-to-weight ratios, which provides both versatility and high adaptability—buildings can be easily repurposed according to changing needs, and so the long-term viability of projects can be ensured.

The issue of steel products reuse and recycling is increasingly being considered by researchers[24–26]. However, although the overall level of steel reuse and recycling in developed countries is approximately 93–95%[27], in most cases it is recycling, and only up to 4–5% of steel products are reused by extending the durability of structures. The main problem with the reuse of metal building products is testing and verification of material properties, and research in this area is currently limited. To evaluate the properties, Fujita and Masuda[28]proposed a non-destructive evaluation procedure. The results obtained by researchers were evaluated according to Japanese standards and found to be in line with the design specification. A study of the reuse of steel structures without

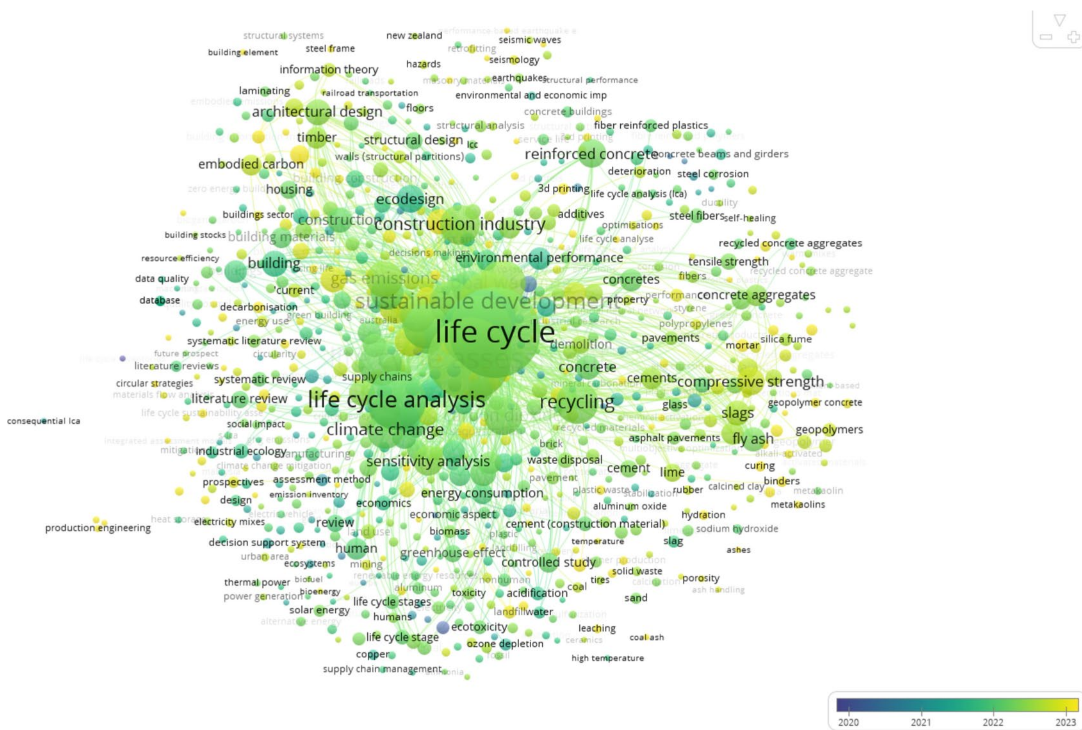

Fig. 1. Clustering of Research Areas between the Most Used Keywords on the Green Deal in Renovation of Buildings in 2020–2024.(Source: VOS viewer mapping of authors' keyword analysis from Scopus database, 10.9.2024).

melting showed that increasing their durability can improve energy efficiency and reduce carbon dioxide emissions by up to 30%[29,30]. The creation of a closed-loop economy should combine the recovery and reuse of steel products from decommissioned buildings. Most research on the reuse of structural materials from old buildings focuses on methods to improve the quantification of recycling and quality indicators rather than on product recovery and direct reuse.

Literature review

Modern practice in the construction industry pays little attention to the possibilities of steel reuse and recycling. In Australia, research by Tucker[31]found that only 11% of steel materials and components from demolished office buildings are reused and only 58% of them are recycled. In addition, 31% of them are thrown into the landfill, which is 45% of the building's embodied energy. In the United Kingdom, the overall average recovery rate for steel from buildings at the end of their life cycle can be as high as 96%[32]. At the same time, reuse of steel products does not exceed 4–15%, depending on the type of material used. Researchers determined the following reasons for such alarmingly low rates of reuse: lack of detailed knowledge of the properties of the product and its history of use (this can be important, for example, if the component has been subjected to fatigue loading[33]), it is difficult to guarantee durability of reusable products[34]and coated products[35], and for light-weighted structures it is difficult to ensure integrity of elements.

When reusing steel, researchers identify a number of problems to be solved. To check the suitability of steel elements obtained during the dismantling of structures as components of products (Brown, D.)[36]a set of measures must be implemented. An audit of the building (the one the steel products were removed from) must be conducted and the date of construction must be indicated in the documentation (the author believes that the date of construction will be close to the date of manufacture of the product). The contractor must establish that the steel element is a derivative of the building structure, which was erected after 1970, and was not subjected to significant dynamic loads, effects of high temperatures during a fire. If necessary, after an external inspection, fault finding of external cracks of welded joints can be carried out by means of using the magnetic powder method in order to make sure that there is no significant loss of the effective section of the steel product due to corrosion (a loss exceeding 5% of the element thickness is considered significant). Next, the supplier must measure the cross-sectional dimensions in at least three locations, if unknown, and compare the resulting geometric sections with the normative ones (BS EN: 1090; 1993; 10,029; 10,034; 10,051; 10,055; 10,056; 10,204; 10,210; 10,219; 10,279). If there are minor deviations, three places along the elements should be selected for comparison with the nominal values. Such a procedure involves significant risks regarding a long-term operation of the used steel elements, and the use of traditional mechanical tests does not guarantee stability of the entire length or section and is associated with partial destruction of the product[37]. Recent research on the use of automated process control systems based on machine learning models[38] is innovative and points to further areas of improvement.

Existing industrial or agricultural buildings were not built with recycling in mind and therefore do not have a high recycling potential—the amount of embodied energy and natural resources used in a building that can be made usable by recycling after demolition. This does not allow for a significant reduction in energy and raw material extraction over the long term when disposing of such structures.

Steel is mostly recyclable and scrap can be turned into steel of the same (or higher or lower) grade depending on the smelting and processing technology. The final economic value of a product is not determined by the recycled steel content, and there are many examples of high value products that contain large amounts of recycled steel. We have conducted a number of studies on the use of recycled metal waste for the production of rolled iron and steel[39,40], including the use of modifiers[41]and evaluated their plasticity[42]. Based on these studies, a hypothesis was formed to create an automated system for reliable inspection, testing of existing structures and their restoration based on an approach using machine learning models and non-destructive testing of properties.

Based on the assessment of existing research, it has been found that there are significant gaps when it comes to predicting properties of steel products at the last stage of the building life cycle—stage D. On the one hand, the existing data sets are quite limited, on the other hand, the development of highly efficient ML models and ensemble models is necessary. This research is aimed at solving this problem, while focusing on the following tasks. The main goal is to evaluate the LCA of a steel component structure and create a reliable ML method that can predict the possibility of reusing the most common structural steel based on the determination of its yield strength ($\sigma_{0.2}$) by means of using a non-destructive magnetic method at stage D of the life cycle of a building structure. To achieve these goals, a reliable experimental data set was collected within this research. This data set was used to predict the change in yield strength of steel after long-term service.

The innovation of the development lies in the ability to provide an automated tool to support informed decision-making for the reuse of building steel for construction site professionals. The accuracy of the ensemble model and its potential for integration with existing practices indicate significant progress in managing steel reuse processes at the final stage of the building life cycle – stage D.

The study aims to bridge the gap between academic research and practical reuse of building steel at the last stage of the building life cycle – stage D. It is proposed to use an automated tool to support informed decision-making for the reuse of building steel after operation based on the use of an ensemble learning model with non-destructive testing of properties.

The research is a significant contribution to the current state of the art in life cycle management of construction steel reuse in stage D. The study fills a critical gap in existing traditional inspection methods (mostly manual) by introducing the use of an ensemble model with non-destructive condition assessment, offering an automated solution in real time. The innovation lies in the ability to retrain the ensemble model on new data sets of different construction steels after various impacts. This allows the control to be adaptable to different building contexts. The research also not only pushes the technological boundaries of the industry, but also has practical implications that could potentially lead to greater use of steel products for post-construction and improve the safety of existing structures after unplanned external impacts.

Material and methods

The materials and methods of this paper, namely the dataset used for the research, and the modeling and evaluation techniques, will be presented in this section.

For research, samples made of construction steel containing 1.36–1.65% Si, 0.56–0.8% Mn (analogues of 13Mn6, 9MnSi5, SB49) were used. This steel is widely used in construction, while the installation of welded structures in the form of beams, channels, bars, corners, sheets and strips. Chemical composition of this steel is shown in Table 1.

To assess the effect of strain load on samples made of the construction steel and establish the relationship between the change in the structural state and the coercive force, systematic studies were conducted in production. Samples of size 6.2 × 20 × 270 mm were selected for researches. The average load (49 KN) that should be applied to create the stress value in the samples corresponding the beginning of plastic deformation of steel ($\sigma_{0,2}$ = 280 MPA) was determined. Samples stretching was performed in increments of 0.1 $\sigma_{0,2}$ = 30MPA on a tensile testing machine (MR, MR-500, Ukraine). To predict properties, the data obtained for a 5-year period at various enterprises are shown in the dataset. Various machine learning models and model ensembles were applied to their processing.

To assess the mechanisms underlying the relationship between ultimate bending strength (MPa) and structurally sensitive characteristic—coercive force (A/cm), a batch of 300 samples was studied. Sampling took place at different intervals of the study period, and samples were cut after testing at each load level. Microfaces were prepared for such samples and the metal microstructure was analyzed.

To estimate the yield strength of samples made of the construction steel by non-destructive testing, the method of measuring the magnetic parameter—the coercive force (H_c, A/cm) was used. The magnetic parameter was evaluated immediately after the load was removed, after 70 h, and after 100 h. Method of conducting coercive force measurements is given in the industry standard 29.32.4–37–532 developed by us. The measurements were carried out using portable magnetic structuroscope–coercimeter (MSC, KRM-C, Kharkiv, Ukraine). The device allows to perform local non-destructive testing (the control area is equal to the cross-sectional area of the device probes) by coercive force in the measurement range of 1.0–60.0 A/cm with an error of not more than 2.5%. The coercive force is measured by controlling the residual magnetic density shift value in a closed magnetic circuit. The circuit is created by a magnetic converter system, the poles of which are closed by the controlled sample. The measurement cycle includes magnetic preparation (duration 2 s), residual magnetization compensation (2 s), H_c calculation, and result indication. During the measurement, the area under the probe of the coercimeter overhead converter is magnetized to saturation with pulses with an amplitude of 3.0 A, after which the residual magnetization field is automatically compensated. The value of the coercive force indicator is calculated according to the value of the compensation field.

Life cycle assessment research

The LCA approach in the European construction sector is regulated by international standards ISO14040:2006 and ISO 14,044:2006. LCA makes it possible to assess the potential environmental impact of building structures and take into account changes in the environment during their life cycle. For the field of construction, the life cycle phases are defined by EN 15,978 and EN 15,804 standards (Fig. 2). The BS EN 15,978:2011 method is likely to be the dominant calculation method used in the construction industry[43], so the life cycle classification in this information document is based on BS EN 15,978:2011.

The Product Stage phases (A1-A3), Construction Process Stage (A4-A5) and Use Stage (B1-B7) phases are sufficiently investigated using the LCA approach[44]. Most researchers focus on the evaluation of individual stages of the life cycle of construction structures, or on the early stage of design[45]. So Moncaster M[46,47]. investigates a tool for estimating carbon and energy costs throughout the life cycle of buildings to be used at an early design stage.

At the same time, the End of Life Stage phases (C1-C4) and especially D—Benefits and Loads Beyond the System Boundary are insufficiently studied. Module D quantifies carbon impacts beyond emissions over the life cycle of a building. It recognizes the concept of “designing for reusing and recycling” as it demonstrates the benefits of reusing, recycling and energy recovery. The research by Eva Martinez[48], devoted to the study of LCA in the End of Life Stage phase of the life cycle of buildings, made it possible to form a set of tools for recording environmental data during various options for demolition of built structures. It has been established that for traditional demolition, the main environmental aspect consists in transportation of waste from the demolition site to the final disposal site. For selective demolition of buildings, the largest impact on LCA is caused during transportation of waste from the demolition site to the treatment plant and during transportation of non-recyclable fractions to the final disposal site, another significant impact is caused during fuel consumption of the hydraulic demolition equipment and the loading and unloading equipment of the treatment plant. The final phase of EC recover (module D) is described as a carbon credit that can be recovered through a certain future use of the materials.

C	Si	Mn	S	P	Ni	Cr	Cu	Fe
0.10–0.12	0.56–0.80	1.36–1.65	0.024–0.030	0.018–0.025	0.020–0.030	0.02–0.30	0,02–0.08	96–97

Table 1. Chemical composition of the construction steel (wt.%).

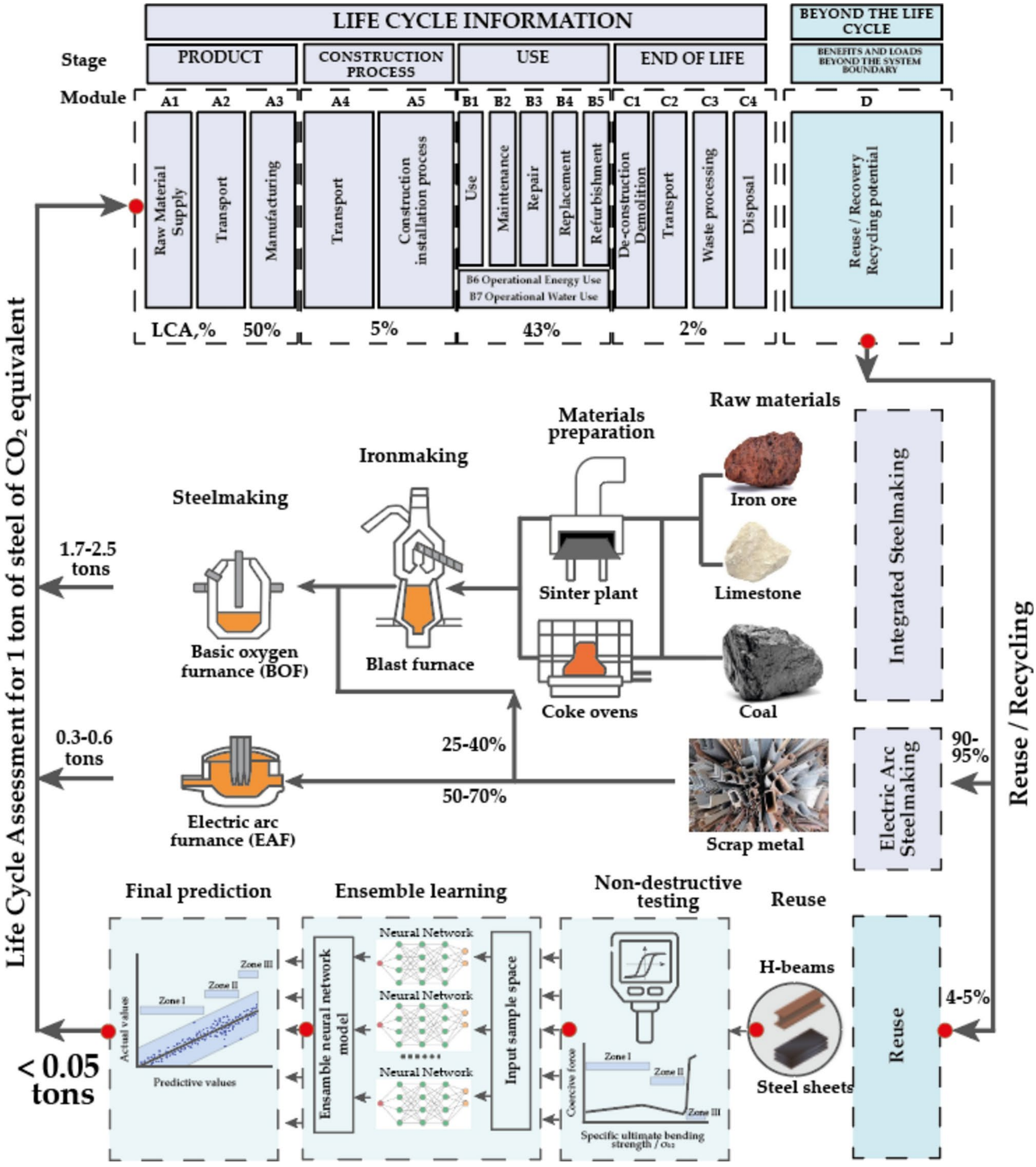

Fig. 2. Building life cycle stages (adapted from BS EN 15,978:2011).

The reason for the small number of publications on Modules C and D is that there are two practical problems associated with conducting an LCA for a building at an early stage. The first problem consists in individuality of the projects of most buildings. This means that the materials and processes will be different for each separate project. Many of them will be determined at later stages of design, and some will be clarified immediately before the start of the construction of the object on site. The second problem is the lack of data for all stages of the life cycle. Presence of trade secrets and the lack of a culture of open data among manufacturers of building materials and components make it difficult to obtain data on the impact of products on the environment throughout the entire life cycle, despite the presence of standards developed in individual countries, in particular such standards as BS EN 15,804[47].

Calculation of Life Cycle Assessment (LCA) indicators was carried out in the Solid-Works Sustainability software environment based on generally accepted approaches[49,50].

International standards ISO 14,040 and ISO 14,044 are used to implement Life Cycle Assessment (LCA) in SolidWorks Sustainability. The ISO 14,040 standard establishes the principles and general framework of life cycle assessment (LCA), it includes definition of purpose and scope, inventory analysis, impact assessment as well as interpretation of results. The 14,044 standard provides detailed requirements and guidance for conducting a life cycle assessment, including data management, life cycle modeling and reporting. SolidWorks Sustainability uses the GaBi LCA Database, which contains detailed data on the environmental impact of various materials, processes, and energy systems. The use of the ISO 14,025 international standard allows SolidWorks Sustainability to regulate transparency and reliability of information about environmental characteristics of the product provided in the form of a declaration. This approach made it possible to carry out an ecologically sound assessment of the materials that make up building structures and provided results that are close to international standards.

This allowed us to conduct an environmental analysis, taking into account the entire life cycle of metal structures, which includes ore mining, material production, use of the structure, end-of-life disposal and all transport between these stages. The input data were taken from the SolidWorks database of materials and their properties, with Material Recycled Content of 18%; 500 km of material transport from production to construction by road freight transport; Manufacturing Electricity of 0.19 kWh/kg; Manufacturing Natural Gas of 1476.6 BTU/kg; Scrap Rate of 9.67%.

ML algorithms

Individual machine learning, were studied and, also, they were combined in ensemble approach to improve the model's stability and predictive power. This allowed to get a higher predictive performance compared to the single model[49–51]. The ensemble[52]finds ways to combine multiple machine learning models into a single predictive model[53–55]. Some models are well suited for modeling data at plastic deformations up to 150 MPa, while others do well with strain intervals close to 250–300 MPa—the Ultimate bending strength limit. Instead of forming a single complex model, the ensemble model learns several simple models and combines its results to make a final decision[56–60]. Combined strength models compensate the individual variations and biases. Ensemble learning will provide a composite prediction when the final accuracy is better than that of individual classifiers.

In the current study, individual machine learning models, after verification were included in 10 ensemble models of WeightedEnsemble_L2 and tested to predict ultimate bending strength based on the non-destructive magnetic control method discussed in the following sections (Fig. 3). The WeightedEnsemble_L2_FULL is a trained regression model whose objective is to minimize the "mean_squared_error" quality metric. 114 rows were included in the evaluation dataset. Scores are calculated using k-fold cross-validation resampling method that train a machine learning algorithm on different subsets of the dataset. A score is then calculated for overall performance by averaging the resulting performance metrics for each trial. First-level ML models were included in the second-level WeightedEnsemble_L2 model if their accuracy on the training sample was equal to or greater than K, where the value of K was determined by the automatic algorithm. It should be highlighted that for assuming ML algorithms, the k-fold cross-validation with different K was used to identify the appropriate K with higher performance[61–65].

We trained several base models. To find the best combination for our dataset, ensemble mode runs 10 trials with different model and hyper parameter settings. Then combines these models using a stacking ensemble method to create an optimal predictive model. We used a Bayesian optimization algorithm to automatically configure machine learning hyperparameters. The effectiveness of its use has been confirmed for solving complex problems with nonconvexity[53], multimodality, and high evaluation costs.

Description of database

In this study, there are a total of 8 data sets on the deformation effect on the structure and magnetic properties of the studied material, which were collected at several enterprises. The data was analyzed based on seven characteristics. These seven characteristics were used as parameters in the following order: ultimate bending strength—target column; value H_c and $\sigma_{st.dev}$ measured immediately after removing the load; H_c and $\sigma_{st.dev}$ after 70 h; H_c and $\sigma_{st.dev}$ after 100 h.

Data normalization

In this paper, forecasting is based on a set of data obtained over a 5-year period at several enterprises. To build a forecasting model and conduct statistical analysis, the results of laboratory experimental tests were applied. In this study, there are a total of 8 data sets from different enterprises on the deformation effect. The data sets used for machine learning had a significant range of values ($\sigma_{0.2}$ = 0–294 MPa, H_c = 3.52–7.45 A/cm, $\sigma_{st.dev}$ = 0.01–0.14). In this case, some machine learning models do not work effectively. Data normalization was used. It is accomplished using the max–min mapping function and takes the following form. In an equation where X_n is normalized data, X_{min} and X_{max} are the minimum and maximum values of each input variable, respectively, and X is the original data set to be normalized. Data normalization has improved the accuracy and stability of the prediction model.

Statistical analysis. To measure machine learning model performance we used the following metrics and validation techniques. Models results were compared to test their effectiveness according to MSE (Mean Squared Error), RMSE (root mean squared error), R^2, and MAE (Mean Absolute Error), which were calculated as follows:

$$\mathbf{MAE} = \frac{\sum_{i=1}^{n} |\mathbf{o_i} - \mathbf{y_i}|}{\mathbf{N}}, \tag{1}$$

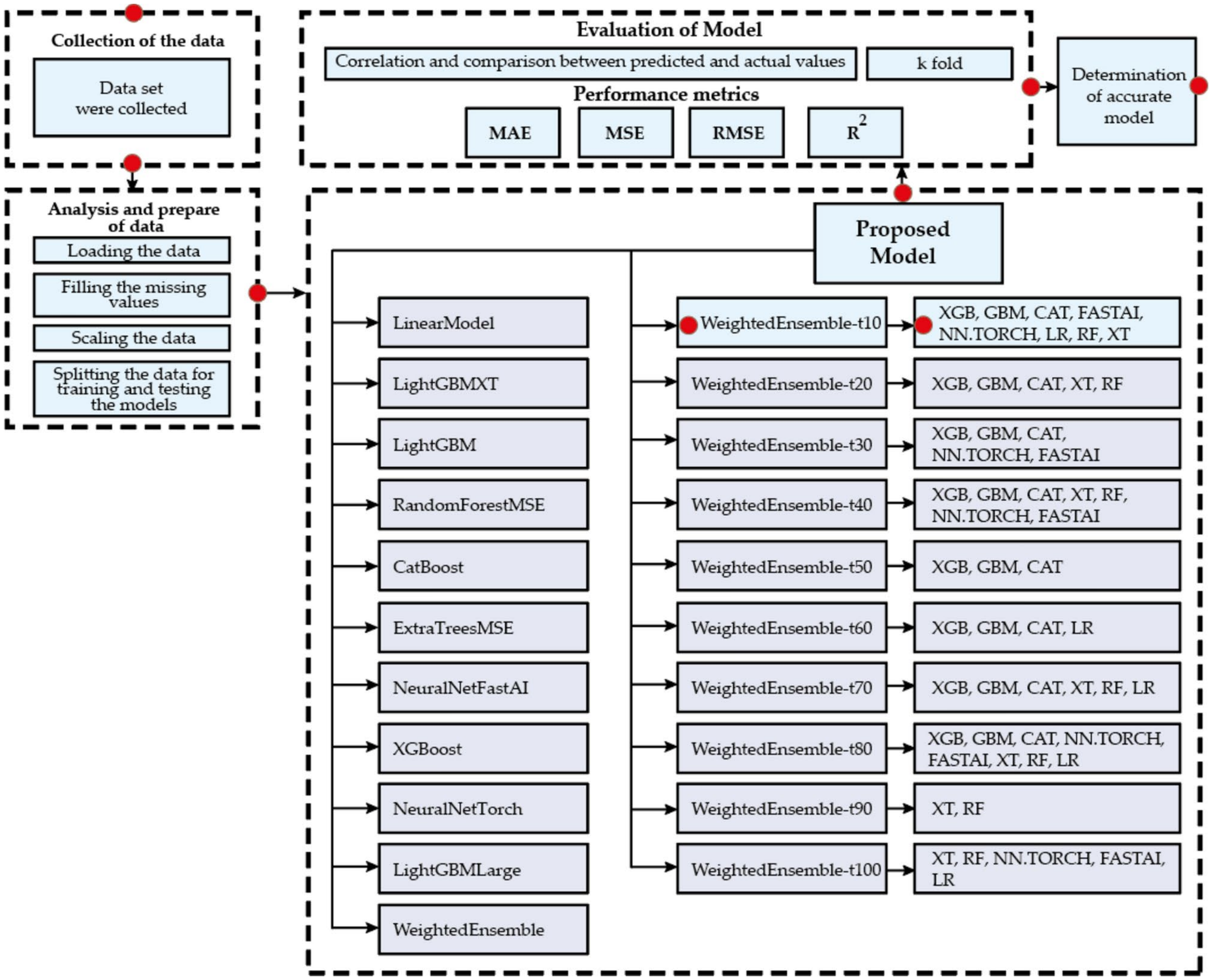

Fig. 3. Flowchart of the methodology of machine learning adopted in the current study.

$$\mathbf{MSE} = \frac{\sum_{i=1}^{n} (o_i - y_i)^2}{N}, \tag{2}$$

$$\mathbf{R}^2 = \left[\frac{\sum (o_i - \overline{o})(y_i - \overline{y})}{\sqrt{(o_i - \overline{o})^2}\sqrt{(y_i - \overline{y})^2}} \right]^2 \tag{3}$$

$$\mathbf{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (o_i - y_i)^2}, \tag{4}$$

where N is the number of samples, and y_i and oi are measured and predicted values, respectively. To determine the deviation, how different the predicted and average values of machine learning models differ, we used the mean absolute error indicator. MAE is defined as the sum of absolute errors divided by the number of observations. The values ranged from 11.55 to 44.30, with smaller numbers indicating that the model matched the data better.

Results and discussion

Our research is part of a comprehensive work on predicting the properties of met-al products by a non-destructive method during their life cycle. In this work, the possibilities of predicting the ductility limit of construction steel by a non-destructive magnetic method—coercive force after applying operational deformations within or equal to the plasticity limit of the material using machine learning algorithms are investigated. In many cases, it is not possible to estimate the load value in advance, and for stable operation of the product, reliable forecast estimates obtained without destruction are necessary.

Life cycle assessment

We performed a Life Cycle Assessment (LCA) for metal materials as part of the steel structures of the elevator tower and an additional grain cleaning unit for grain storage facility with a capacity of 22.4 thousand tonnes (2nd start-up complex for 18 thousand tonnes) in Murafa village, Kharkiv region. The total weight of the metal is 12.95 tonnes (Table 2). The structure includes: bent steel channels with equal shelf lengths—1.35 tonnes; square steel pipes—6.49 tonnes; angle steel flutes—2.02 tonnes; heavy plate steel—1.07 tonnes; corrugated steel—1.86 tonnes; I-beams for suspended walkways—0.16 tonnes. The metal of grains weight of the bins is 3,839 tonnes. The environmental life cycle analysis resulted in the following environmental indica-tors and environmental impact indicators: Carbon Footprint (kg CO_2), Energy Consumption (MJ), Air Acidification (kg SO_2), Water Eutrophication (kg PO_4).

A comparative analysis of the contribution of the main factors, expressed as a percentage, to the final environmental assessment of the LCA of metal structures for periods from the beginning of construction—8 years and for the period of resource ex-tension after non-destructive testing and extension of the building's service life to the projected period of 30 years was carried out. Scenarios used: A—baseline scenario for a new building after 1 year of operation; B—scenario of a traditional linear approach of demolishing a building in a short time and building a new structure, in which the emissions from the recycling of the remaining materials are added to the indicators of the new building; C—scenario in which, after the proposed measures, the operation of the building is extended to the planned 30 years.

It was found that the main contribution of 81.05–90.20% to the formation of the Car-bon Footprint (37,611 kg CO_2), Energy Consumption (505639 MJ), Air Acidification (116 kg SO^2), Water Eutrophication (17 kg PO_4) is made by the costs of raw material extraction and steelmaking. The percentage of the production process associated with the moulding of the material is much lower: Carbon Footprint—9.22%, Energy Consumption—12.36%, Air Acidification—11.98%, and the smallest impact is for Water Eutrophication—3.66%. Taking into account that the End of Life period for steels is associated with recycling in the adopted calculation option—95%, and only a small share is recycled, the value of its contribution ranges from 4.06–5.57% for Water Eutrophication and Air Acidification, and does not exceed 2.5–2.6% for Carbon Footprint and Energy Consumption. Taking into account that the transport was carried out from domestic steel producers, which ensures circularity in the supply chain, the share of the transport component is insignificant and ranges from 1.04–2.12%.

Name of the Structural Element (Weight, Tonne)	Name of the Component	Carbon Footprint (kg CO_2)	Energy Consumption (MJ)	Air Acidification (kg SO_2)	Water Eutrophication (kg PO_4)
Bent steel channels (weight 1.35 tonnes); steel square tubes (weight 6.49 tonnes); equal angle steel (weight 2.02 tonnes)	Material	1.786	23.569	0.0050	0.00050
	Manufacturing	0.211	3.784	0.0009	4.30E-05
	End Of Life	0.057	0.799	0.0004	4.77E-05
	Transportation	0.024	0.349	0.0001	2.49E-05
	Total*	**20,483.657**	**281,025.776**	**62.6697**	**5.7488**
Steel plates (weight 1.07 tonnes)	Material	2.037	25.981	0.0066	0.001904
	Manufacturing	0.212	3.808	0.0009	4.33E-05
	End Of Life	0.058	0.805	0.0004	4.80E-05
	Transportation	0.024	0.351	0.0001	2.50E-05
	Total*	**2494.106**	**33,111.364**	**8.4599**	**2.1618494**
Corrugated steel sheet (weight 1.86tonnes)	Material	2.101	27.429	0.0054	0.000522
	Manufacturing	0.2123	3.812	0.0008	4.34E-05
	End Of Life	0.058	0.8058	0.0004	4.81E-05
	Transportation	0.024	0.351	0.0001	2.51E-05
	Total*	**4455.146**	**60,259.722**	**12.4549**	**1.18768812**
I-beams for suspended guides (weight 0.16 tonnes)	Material	1.839	24.184	0.0053	0.000483
	Manufacturing	0.213	3.818	0.0009	4.34E-05
	End Of Life	0.058	0.807	0.0004	4.82E-05
	Transportation	0.024	0.352	0.0001	2.51E-05
	Total*	**341.272**	**4665.632**	**1.0671**	**0.09592416**
Metal tanks (weight 1.86t)	Material	2.269	28.007	0.0068	0.00192376
	Manufacturing	0.212	3.808	0.0008	4.33E-05
	End Of Life	0.0579	0.805	0.0004	4.80E-05
	Transportation	0.0237	0.3507	0.0001	2.50E-05
	Total*	**9836.938**	**126,576.053**	**31.3431**	**7.83217424**
Total result		**37,611.120**	**505,638.547**	**115.994**	**17.026**

Table 2. Results of the Calculation of Life Cycle Assessment Indicators for the Elevator Tower and the Additional Grain Cleaning Unit for a Grain Storage Facility with a Capacity of 22.4 thousand tonnes (2nd Start-up Complex for 18 thousand tonnes) for the First Year of Commissioning.

Extending the service life of metal structures without recycling them can significantly improve the environmental performance of the LCA life cycle. Let's consider 3 scenarios. Scenario A is a baseline with indicators for a new building after 1 year of operation. The second scenario B is when, after a critical impact, structural deformation occurs and after 8 years of operation, the commercial building is demolished and rebuilt in accordance with the traditional linear process. For Scenario B, the emissions from material recycling are added to the new building's performance, as they cannot be used directly in the production of new steel batches. The third scenario—after the inspection, non-destructive methods are used to identify areas for which restorative actions are taken (welding, replacement of highly loaded structural fragments) and the building's service life is extended to the planned 30 years. In this case, the indicators are significantly lower. According to the calculations, Scenario B is the most costly and negative in terms of environmental impact. Scenario C is the most efficient, with minimal environmental impact indicators. In this scenario, the time for putting the facility into commercial operation is also minimal, so the use of non-destructive testing to assess metal damage with the use of machine learning methods to predict the remaining service life is a timely and relevant area.

Dependence of the coercive force level on the steel load

The dependence of the coercive force level on the steel load was evaluated. It is established that for the curve H_c the tensile loads of construction steel are characterized by three zones (Fig. 4). When loaded from the initial state to 0.5–0.6 $\sigma_{0.2}$, a uniform increase in the coercive force occurs according to the dependence (R = 0.89):

$$H_c = 3.55 + 0.54N\sigma_{0.2} \tag{5}$$

where $N\sigma_{0,2}$ is the load value relative to $\sigma_{0,2}$ of the material. In this dependence, the free term characterizes the level of coercive force (has dimension [A/cm]), which corresponds to the structural state of hot-rolled steel without load. The coefficient of 0.54 characterizes the intensity of changes in the coercive force from the level of loads in the elastic area and has the dimension [$N\sigma_{0.2}$/MPa]. This zone is characterized by a predominant effect on the NS level of elastic stresses during sample stretching.

The second zone (0.6–0.9 $\sigma_{0,2}$) is characterized by magnetic index uneven distribution. The decrease in H_c level to 3.5–3.65 A/cm is due to metal deformation in local micro-volumes. This assumption is confirmed by a decrease in the spread of magnetic parameter values up to 4 times (the root-mean-square deviation decreased from 0.12 A/cm (0.6 $\sigma_{0,2}$) to 0.03 A/cm at 0.7 $\sigma_{0,2}$) in the zones of such deformation. In the zone of loads that is close to the beginning of plastic deformation (0.95–1 $\sigma_{0,2}$), a significant increase in the level of coercive force occurs (1.5–2 times compared to the derivative state). This is due to changes in the material structural state and increase in the level of its defect. H_c level change for such a zone can be described by the following equation (R = 0.89):

$$H_c = 4.14 + 37.1N\sigma_{0.2}, \tag{6}$$

where $N\sigma_{0,2}$ is the load value relative to $\sigma_{0,2}$ of the material. The free term characterizes the level of coercive force corresponding to the structural state in the field of elastic stresses and local deformations under a load of

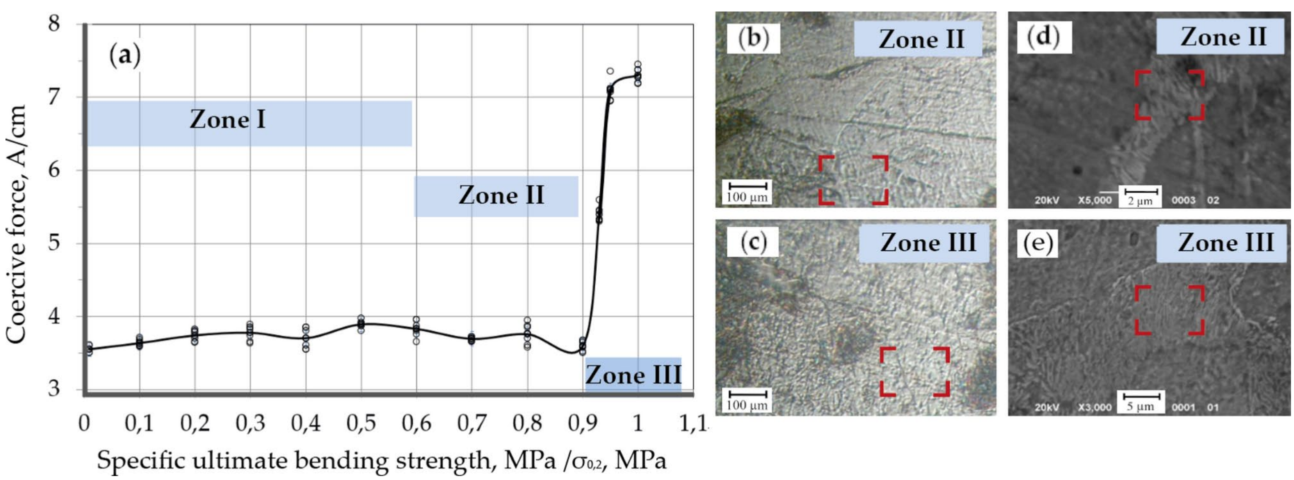

Fig. 4. H_c dependence of construction steel on the load value relative to its Yield Strength ($\sigma_{0.2}$) with zones indication (**a**) where the relationships nature is changed. Microstructure of the construction steel: (**b**) – the beginning of individual ferrite grains deformation after a load of 0.5 $\sigma_{0.2}$ (Zone I); (**c**) – almost all ferrite grains are deformed after a load of 0.7 $\sigma_{0.2}$ (Zone II); (**d**) – the perlite component is not affected after a load of 0.5 $\sigma_{0,2}$ (Zone I); (**e**) – the perlite component is decorated with inclusions after the load of 0.7 $\sigma_{0,2}$ (Zone II). Microstructure images (**b, c**) obtained in polarizing light using a metallographic microscope, and images (**d**) and (**e**) obtained by electron microscopy. The most characteristic areas corresponding to Zone II and Zone III are highlighted in red, respectively. Etching with 4% HNO_3 solvent.

4.7–4.9 t. The coefficient 37.1 characterizes the intensity of changes in the coercive force depending on the level of loads in the area of elastic and plastic deformations. The intensity of increasing of H_c coefficient of change for this zone is almost 70 times higher than elastic deformations (the first zone), which indicates the intensity of changes in the structural state of the material under the loads impact.

Data visualization

The data was analyzed based on seven characteristics: ultimate bending strength—target column; value H_c and $\sigma_{st.dev}$ measured immediately after removing the load; H_c and $\sigma_{st.dev}$ after 70 h; H_c and $\sigma_{st.dev}$ after 100 h and their distribution is illustrated in Fig. 5.

Machine learning algorithms and ensemble learning

The correlation matrix of the dataset is presented in Fig. 6. The results of machine learning models were compared to test their performance according to the MSE (Mean Squared Error), RMSE (Root mean squared error), R^2, and MAE (Mean Absolute Error) metrics (Table 3, 4) and (Fig. 7).

The main focus of this study was on using the capabilities of machine learning (ML) algorithms to solve the problem of predicting the reuse of construction steel based on the determination of its yield strength by the non-destructive magnetic method. Table 3 compares the algorithms of the models LightGBMXT, LightGBM, RandomForestMSE, CatBoost, ExtraTreesMSE, NeuralNetFastAI, XGBoost, LinearModel, NeuralNetTorch, and LightGBMLarge to solve this problem. However, the use of ensemble learning significantly improved the quality and accuracy of the results, demonstrating its advantage in combining several models to obtain more accurate predictions. We performed the optimization The results of the WeightedEnsemble ensemble method (10 models were analyzed) allowed us to obtain the best prediction accuracy (MSE = 441 MPa and RMSE = 21 MPa). Verification of the modeling results confirmed the reliability of the data obtained. In addition, with high accuracy, a low inference delay (IL = 0.119 s) was obtained when predicting the tensile strength (MPa) based on the data of non-destructive testing of structural steel products. This makes it possible to automate the inspection process and obtain more accurate data in real-world conditions.

Despite the possibility of justifying individual areas of the coercive force on plastic deformation dependence at the level of a small data sample, it is not an easy task to develop a model for predicting ultimate bending strength (MPa) using a non-destructive method Therefore, it is rational to use more flexible forecasting models based on machine learning. The best performance of the ML model is indicated by MAE values closer to 0. Value R^2 approaching 1 indicates better modeling, while MSE, RMSE, and MAE values approaching 0 indicate better modeling. We used a nonlinear correlation of functions based on the Spearman rating ratio. The strongest positive correlation was found between ultimate bending strength ($\sigma_{0,2}$) and indicators of coercive force (H_c) after 100 h ($R^2 = 0.76$) and 70 h ($R^2 = 0.68$) after removing the load. While the standard deviation of coercive force (H_c) after removing the load correlates with the levels of the magnetic parameter after 70 h ($R^2 = 0.67$) and 100 h ($R^2 = 0.53$). This confirms our assumption that the material relaxation processes occur after the load is removed.

The smallest deviations of forecast data from the input data (MSE = 441 MPa and RMSE = 21 MPa) has an ensemble of WeightedEnsemble-t10 models. Despite a significant number of models-eight included in such ensemble—it has a low Inference Latency (IL = 0.119 s), i.e. the time it takes for ensemble of machine learning models to make its prediction after being given input information. The lowest Inference Latency index (IL = 0.101 s and IL = 0.111 s) is found in the WeightedEnsemble-t30 ensembles and the WeightedEnsemble-t90 ensemble, but they have lower accuracy, the error rate is up to 20%. Due to the combination of prediction accuracy and Inference Latency, the most acceptable ensemble of WeightedEnsemble-t10 models was established. This particular ensemble is further called WeightedEnsemble and is further compared to machine learning models.

For the studied machine learning models, the best result is a tree-based algorithm that uses several decision trees on the entire dataset model ExtraTreesMSE-L1 (L1 – lasso regularization), for which MAE = 11.55 MPa. In this model, trees are randomly divided at each level. The decisions of each tree are averaged to prevent overfitting and improve forecasts. Each decision tree generates one forecast, and the final one is based on the majority forecast. Additional trees add some degree of randomization compared to the random forest algorithm. Despite the best MAE score, the ExtraTreesMSE-L1 model loses out in accuracy to the WeightedEnsemble-L2 ensemble (by 20.2% in MSE and 9.7% in RMSE). LinearModel has the greatest deviations (MAE = 44.30 MPa).

To check the compliance of the model, taking into account significant errors in forecasting, we used the root – mean-square error-MSE, which was defined as the average square of the difference between the actual and forecast values.

For the studied models, the root-mean-square error ranged significantly up to 645%. LinearModel models showed the worst match for significant deviations (MSE = 2846MPa^2) and NeuralNetFastAI (MSE = 2846MPa^2). And the best performance is the NeuralNetTorch machine learning model (MSE = 474MPa^2) and the optimal values for this data set are the Weighted Ensemble model ensemble (MSE = 441MPa^2).

Using the root Mean Squared Error (RMSE) allowed us to estimate the deviation of forecast data in the same dimension as the base parameter—ultimate bending strength (MPa). As expected, given the MSE metric, the LinearModel machine learning models (RMSE = 53.35 MPa) and NeuralNetFastAI (RMSE = 29.43 MPa) have the greatest deviations. The group for deviations of 24–26 MPa included several models based on RandomForestMSE (RMSE = 25.45 MPa), XGBoost (RMSE = 24.18 MPa) and two models with tree-based algorithms with gradient boosting – whose hyperparameters are adapted to work with large models LightGBMLarge (RMSE = 25.04 MPa) and with default hyperparameters LightGBM (RMSE = 24.81 MPa). The weighted ensemble model ensemble (RMSE = 21.01 MPa) and the NeuralNetTorch model (RMSE = 21.78 MPa) have the most accurate forecast.

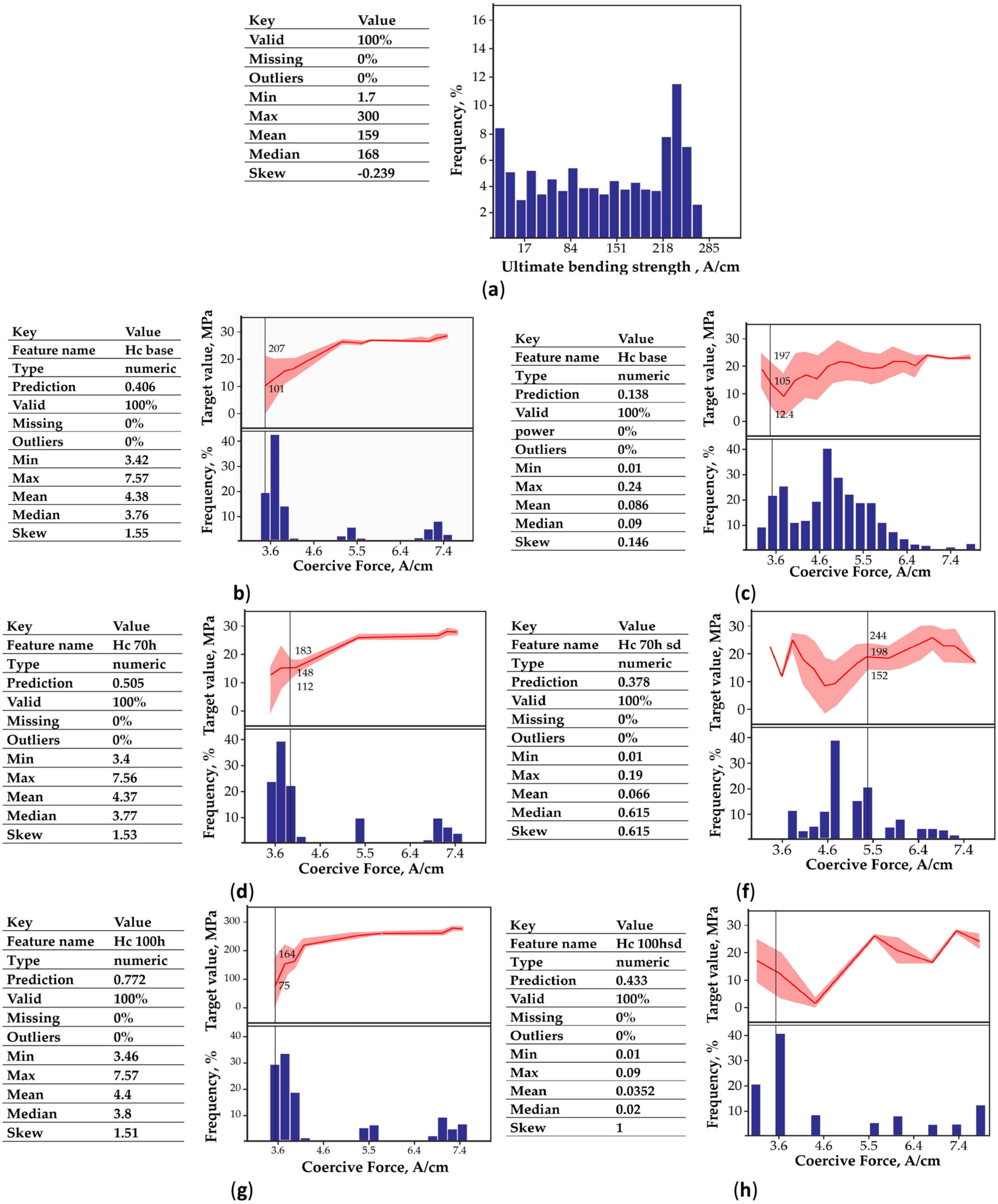

Fig. 5. Feature details and histogram with the corresponding target distribution: (**a**) histogram of the target column—ultimate bending strength (MPa); (**b**, **c**) H_c and $\sigma_{st.dev}$; (**d**, **f**) H_c and $\sigma_{st.dev}$ after 70 h; (**g**, **h**) H_c and $\sigma_{st.dev}$ after 100 h. The lower plot provides the feature distribution and the upper—the corresponding target average with a confidence band of one standard deviation.

Using the R^2 metric the proportion of variance of the regression model recall variable that can be explained by predictive variables was taken into account. If the RMSE indicator allowed to take into account the typical distance between the forecast and actual values, then R^2 allowed to determine how well predictor variables can explain the deviation of the recall variable. For the studied machine learning models, the effect of the magnetic

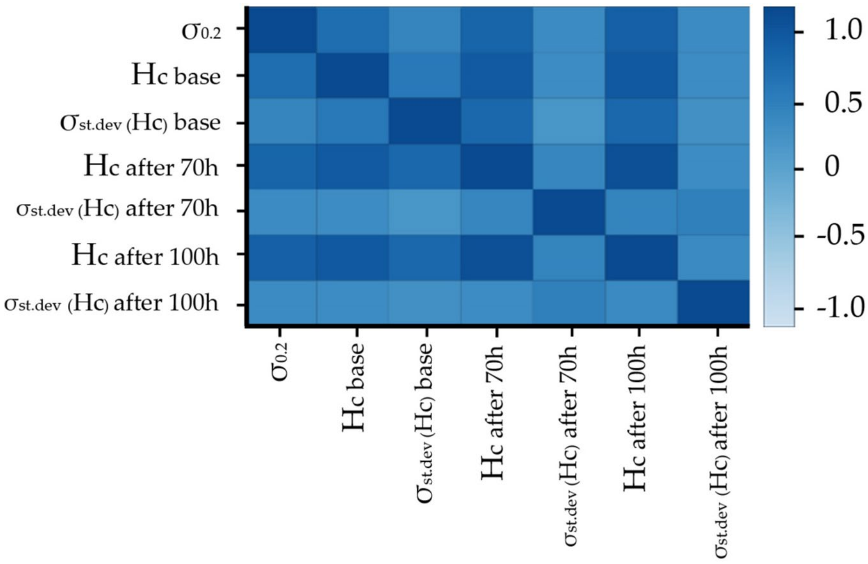

Fig. 6. Correlation matrix of dataset: ultimate bending strength (MPa)—target column; value H_c and $\sigma_{st.dev}$ measured immediately after removing the load; H_c and $\sigma_{st.dev}$ after 70 h; H_c and $\sigma_{st.dev}$ after 100 h.

Name models*	MSE (MPa^2)	MAE (MPa)	RMSE (MPa)	R^2
LightGBMXT	542.376	14.035	23.289	0.933
LightGBM	615.544	13.511	24.810	0.924
RandomForestMSE	647.449	11.647	25.445	0.919
CatBoost	517.752	13.147	22.754	0.936
ExtraTreesMSE	530.909	**11.554**	23.041	0.934
NeuralNetFastAI	866.033	18.766	29.428	0.893
XGBoost	584.874	12.661	24.184	0.928
LinearModel	2846.089	44.360	53.349	0.648
NeuralNetTorch	474.634	12.063	21.786	0.941
LightGBMLarge	626.972	12.717	25.039	0.922
WeightedEnsemble	**441.174**	11.746	**21.004**	**0.945**

Table 3. Comparison of studied ML algorithms.

Ensemble models	ML model types*	MSE (MPa^2)	IL (sec)	RMSE (MPa)	MAE (MPa)
WeightedEnsemble-t10	XGB, GBM, CAT, FASTAI, NN.TORCH, LR, RF, XT	**441.174**	0.119	**21.004**	11.746
WeightedEnsemble-t20	XGB, GBM, CAT, XT, RF	510.197	0.139	22.588	11.554
WeightedEnsemble-t30	XGB, GBM, CAT, NN.TORCH, FASTAI	505.81	**0.101**	22.49	12.815
WeightedEnsemble-t40	XGB, GBM, CAT, XT, RF, NN.TORCH, FASTAI	501.795	0.154	22.401	12.984
WeightedEnsemble-t50	XGB, GBM, CAT	499.161	0.204	22.342	12.045
WeightedEnsemble-t60	XGB, GBM, CAT, LR	458 945	0.145	21.423	12.258
WeightedEnsemble-t70	XGB, GBM, CAT, XT, RF, LR	499.161	0.204	22.342	11.434
WeightedEnsemble-t80	XGB, GBM, CAT, NN.TORCH, FASTAI, XT, RF, LR	458.943	0.145	21.423	12.258
WeightedEnsemble-t90	XT, RF	449.465	0.111	21.206	**11.434**
WeightedEnsemble-t100	XT, RF, NN.TORCH, FASTAI, LR	441.235	0.162	21.006	11.671

Table 4. Proven model ensembles WeightedEnsemble_L2_FULL. Designation:* IL—Inference Latency; RF—Random Forest, XGB—XGBoost, GBM—LightGBM, CAT—CatBoost, XT – Extra Trees, LR—Linear Models, FASTAI—Neural network fast.ai, NN.TORCH—Neural network Torch.

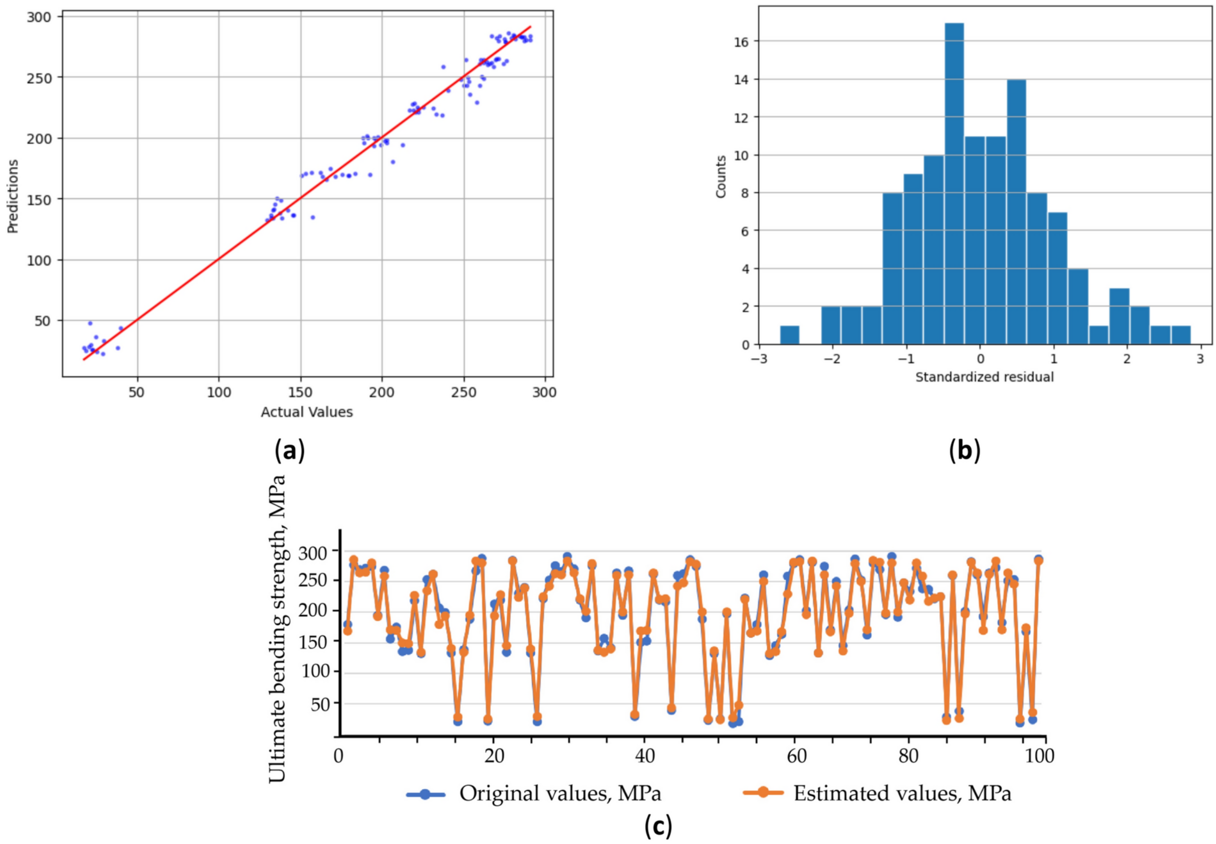

Fig. 7. Prediction based on regression model WeightedEnsemble_L2: (**a**) Actual vs predicted plot; (**b**) Residual histogram. Original and estimated values of regression model WeightedEnsemble_L2 (**c**).

parameter level, the coercive force (A /cm), and the mean-square spread of its values measured immediately after stretching the samples after 70 h and 100 h on the ultimate bending strength (MPa) is better ($R^2 = 0.94$) for NeuralNetTorch. For the Weighted Ensemble model ensemble, predictor variables can explain the deviation of the variable in 95% of cases ($R^2 = 0.95$), which again demonstrates the advantages of this approach in forecasting over using individual machine learning models.

Prospects for further research. The current work has several limitations that should be addressed in future research. Thus, due to the limited number of valid non-destructive testing (NDT) data sets in the current study, the experimental data set does not include a wide range of other structural steels in addition to the investigated steel. Such steels will differ in chemical composition and technologies for ensuring a complex of mechanical properties, which will need to be studied separately after conducting a larger number of experimental works for each grade of steel. This data set also does not include data on the high-temperature impact of an open flame due to a fire on the structural-phase composition of steel, which is possible for assessment at the last stage of the building's life cycle—stage D. In our opinion, steel materials after such high-temperature exposure can only be used as a charge for steel smelting, due to the difficulty of predicting their durability without expensive destructive evaluation methods. For future forming a database of ML-models for non-destructive evaluation of materials for the End of Life Stage (C1-C4) phase and D—Benefits and Loads Beyond the System Boundary phase, it is necessary to ensure the possibility of direct calculation of the mechanical properties of steels and unify the test methods.

Conclusions

Previous studies have confirmed effectiveness of using Life Cycle Assessment at the early stage of building design and when forecasting the environmental impact of new buildings. However, there is considerable concern about the effectiveness of such forecasting in the End of Life Stage (C1-C4) phase and especially D—Benefits and Loads Beyond the System Boundary phase for already existing structures, which are mostly unique projects and can be modernized, rebuilt during their life cycle. In this study, empirical data were collected for LCA assessment and development of a reliable and accurate model for predicting the reusability of structural steel based on determination of its yield point by means of non-destructive magnetic method at the final stages of the construction object's life cycle. A grain storage with a capacity of 22.4 thousand tons, consisting of mainly metal structures of the elevator tower and an additional grain cleaning plant with a total weight of 12.95 tons of metal, was studied. The input variables are the value of the magnetic parameter and the scatter of the measurement results, and the output variable is the level of stresses formed under variable loading in the range from zero to the yield point of steel samples (up to 280 MPa). For forecasting, a series of experimental studies were conducted and processing was performed using machine learning methods.

Although the use of 10 machine learning algorithms, apart from Linear Model and NeurealNetFastAI, were found to be satisfactory in terms of accuracy (above 0.89), it was found that the use of ensemble learning significantly increased accuracy of the model. Regression accuracy increased up to 0.945 after using ensemble learning, and after additional hyperparameter optimization it reached the level of 0.984. and the mean-root error (MSE) decreased significantly.

The main conclusions of this study are that regression algorithms using ensemble learning can accurately predict the level of stresses in metal products of buildings at the end-of-life stages, and in group with them these regression algorithms can predict durability in operation when reused. In general, the results of this study showed that the future formation of a database of ML-models of non-destructive evaluation of materials in the End of Life Stage (C1-C4) phase and D—Benefits and Loads Beyond the System Boundary phase is possible and it requires a further research of a wide range of other construction steels and their production technologies.

Data availability

Abstracted data is available from the corresponding autor on reasonable request.

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References

1. An Official Website of the European Union. A European Green Deal. (accessed on 25 November 2023); Available online: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en
2. Kukharets, V. et al. European green deal: The impact of the level of renewable energy source and gross domestic product per capita on energy import dependency. *Sustainability* **15**, 11817. https://doi.org/10.3390/su151511817 (2023).
3. Hutsol, T. European green deal: Improving the efficiency of using planetary hydraulic machines. *Energies* **16**, 6481. https://doi.org/10.3390/en16186481 (2023).
4. Rahnama, H., Johansen, K., Larsson, L. & Rönnbäck, A. Ö. Collaboration in value constellations for sustainable production: The perspective of small technology solution providers. *Sustainability* **14**, 4794. https://doi.org/10.3390/su14084794 (2022).
5. Kumar, R. et al. Progress in sustainable recycling and circular economy of tungsten carbide hard metal scraps for industry 5.0 and onwards. *Sustainability* **15**, 12249. https://doi.org/10.3390/su151612249 (2023).
6. Ali, A. & Xiao, J. Estimation and minimization of embodied carbon of buildings: A review. *Buildings* **7**(1), 5. https://doi.org/10.3390/buildings7010005 (2017).
7. Lesnyak, E. et al. Applied digital twin concepts contributing to heat transition in building, campus, neighborhood, and Urban scale. *Big Data Cogn. Comput.* **7**, 145. https://doi.org/10.3390/bdcc7030145 (2023).
8. Sakhatsky, V. et al. Determining a technique for transmitting measuring data on the spatial positioning of the piercing head in small-size installations during controlled soil piercing. *East.-Eur. J. Enterp. Technol.* **5**(107), 32–40. https://doi.org/10.15587/1729-4061.2020.212345 (2020).
9. Nolasco, E. et al. Characterization of solid wastes as a tool to implement waste management strategies in a university campus. *IJSHE* **22**(2), 217–236. https://doi.org/10.1108/IJSHE-12-2019-0358 (2021).
10. Yeheyis, M. et al. An overview of construction and demolition waste management in Canada: A lifecycle analysis approach to sustainability. *Clean Techn. Environ. Policy* **15**(1), 81–91. https://doi.org/10.1007/s10098-012-0481-6 (2013).
11. Kibert, C. J. *Sustainable Construction: Green Building Design and Delivery* 5th edn, 656 (Wiley, 2022). ISBN: 978-1-119-70645-8
12. Shehadeh, A., Alshboul, O. & Tamimi, M. Integrating climate change predictions into infrastructure degradation modelling using advanced markovian frameworks to enhanced resilience. *J. Environ. Manag.* **368**, 122234. https://doi.org/10.1016/j.jenvman.2024.122234 (2024).
13. Hopkinson, P., Chen, H.-M., Zhou, K., Wang, Y. & Lam, D. Recovery and reuse of structural products from end-of-life buildings. *Proc. Inst. Civ. Eng. – Eng. Sustain.* **172**(3), 119–128. https://doi.org/10.1680/jensu.18.00007 (2019).
14. Zabek, M., Jegen, P. & Kreiss, L. Introducing a novel concept for an integrated demolition waste recycling center and the establishment of a stakeholder network: A case study from Germany. *Sustainability* **16**(10), 3916. https://doi.org/10.3390/su16103916 (2024).
15. Finamore, M. & Oltean-Dumbrava, C. Circular economy in construction - findings from a literature review. *Heliyon* **10**(15), e34647. https://doi.org/10.1016/j.heliyon.2024.e34647 (2024).
16. Marin, J., Alaerts, L. & Van Acker, K. A materials bank for circular leuven: How to monitor 'Messy' circular city transition projects. *Sustainability* **12**(24), 10351. https://doi.org/10.3390/su122410351 (2020).
17. Cai, G. & Waldmann, D. A material and component bank to facilitate material recycling and component reuse for a sustainable construction: Concept and preliminary study. *Clean Techn. Environ. Policy* **21**(10), 2015–2032. https://doi.org/10.1007/s10098-019-01758-1 (2019).
18. Timm, F. G. J., Passuello, A., Moraga, G. Employing Circular Economy Principles to Enhance Sustainability in the Built Environment. In *Materials Selection for Sustainability in the Built Environment* 87–115 (Elsevier, 2024) https://doi.org/10.1016/B978-0-323-95122-7.00005-8.
19. Afzal, M. et al. Delving into the digital twin developments and applications in the construction industry: A PRISMA approach. *Sustainability* **15**, 16436. https://doi.org/10.3390/su152316436 (2023).
20. Alshboul, O., Al Mamlook, R. E., Shehadeh, A. & Munir, T. Empirical exploration of predictive maintenance in concrete manufacturing: Harnessing machine learning for enhanced equipment reliability in construction project management. *Comput. Ind. Eng.* **190**, 110046. https://doi.org/10.1016/j.cie.2024.110046 (2024).
21. Joița, D. et al. The European dilemma—energy security or green transition. *Energies* **16**, 3849. https://doi.org/10.3390/en16093849 (2023).
22. D'Amico, R. D., Addepalli, S. & Erkoyuncu, J. A. Industrial insights on digital twins in manufacturing: Application landscape, current practices, and future needs. *Big Data Cogn. Comput.* **7**, 126. https://doi.org/10.3390/bdcc7030126 (2023).
23. Lucchi, E. Energy and climatic performances of modern architecture: A complete overview of building physics implications. *Eng. Proc.* **53**, 19. https://doi.org/10.3390/IOCBD2023-15203 (2023).
24. Rečka, L., Máca, V. & Ščasný, M. Green deal and carbon neutrality assessment of czechia. *Energies* **16**, 2152. https://doi.org/10.3390/en16052152 (2023).
25. Luzan, S. O. & Luzan, A. S. Microstructure and abrasive wear resistance of deposited materials of the Ni–Cr–B–Si system with inclusions of dispersed phases. *Mater. Sci.* **56**(3), 381–388. https://doi.org/10.1007/s11003-020-00441-x (2020).

26. Kim, S. & Kim, S.-A. Framework for designing sustainable structures through steel beam reuse. *Sustainability* **12**, 9494. https://doi.org/10.3390/su12229494 (2020).
27. Fujita, M. & Masuda, T. Application of various NDT methods for the evaluation of building steel structures for reuse. *Materials* **7**, 7130–7144. https://doi.org/10.3390/ma7107130 (2014).
28. Rajulwar, V. V. et al. Steel, aluminum, and FRP-composites: The race to zero carbon emissions. *Energies* **16**, 6904. https://doi.org/10.3390/en16196904 (2023).
29. Zurnadzhy, V. I. et al. Tailoring strength/ductility combination in 2.5 wt% Si-alloyed middle carbon steel produced by the two-step Q-P treatment with a prolonged partitioning stage. *Mater. Sci. Eng.: A* **791**, 139721. https://doi.org/10.1016/j.msea.2020.139721 (2020).
30. Huang, B., Xing, K. & Rameezdeen, R. Exploring embodied carbon comparison in lightweight building structure frames: A case study. *Sustainability* **15**, 15167. https://doi.org/10.3390/su15201516 (2023).
31. Tucker, R. et al. Overcoming barriers to the reuse of construction waste material in Australia: a review of the literature. *Int. J. Constr. Manag.* **17**, 1–10. https://doi.org/10.1080/15623599.2016.1192248 (2016).
32. Sansom, M. & Avery, N. Briefing: Reuse and recycling rates of UK steel demolition arisings. *Proc. Inst. Civ. Eng. - Eng. Sustain.* **167**(3), 89–94. https://doi.org/10.1680/ensu.13.00026 (2014).
33. Chen, H.-M. et al. Reclaiming structural steels from the end of service life composite structures for reuse – an assessment of the viability of different methods. *Dev. Built Environ.* **10**, 100077. https://doi.org/10.1016/j.dibe.2022.100077 (2022).
34. Gupta, S., Jha, K. N. & Vyas, G. Construction and demolition waste causative factors in building projects: Survey of the Indian construction industry experiences. *Int. J. Constr. Manag.* **24**(4), 432–442. https://doi.org/10.1080/15623599.2022.2111962 (2024).
35. Efremenko, B. V. et al. Kinetics of structure transformation in pulsed plasma high-Cr coatings under post-heat treatment. *Funct. Mater.* **27**, 117–124. https://doi.org/10.15407/fm27.01.117 (2020).
36. Brown, D. Structural steel reuse: Assessment, testing and design principles.; SCI publication. The steel construction in **72** (2019)
37. Kanyilmaz, A. et al. Reuse of steel in the construction industry: Challenges and opportunities. *Int. J. Steel Struct.* **23**(5), 1399–1416. https://doi.org/10.1007/s13296-023-00778-4 (2023).
38. Shehadeh, A., Alshboul, O. & Almasabha, G. Slope displacement detection in construction: An automated management algorithm for disaster prevention. *Expert Sys. Appl.* **237**, 121505. https://doi.org/10.1016/j.eswa.2023.121505 (2024).
39. Skoblo, T. S. et al. Specific features of the formation of structures in 60KH2N4GMF precipitation-hardening steel. *Mater. Sci.* **47**(5), 644–650 (2012).
40. Vlasenko, T. et al. Increasing exploitation durability of two-layer cast mill rolls and assessment of the applicability of the XGBoost machine learning method to manage their quality. *Materials* **17**(13), 3231. https://doi.org/10.3390/ma17133231 (2024).
41. Vlasovets, V. et al. Improving the performance properties of eutectoid steel products by a complex effect. *Materials* **15**, 8552. https://doi.org/10.3390/ma15238552 (2022).
42. Vlasovets, V. et al. Effect of various factors on the measurement error of structural components of machine parts materials microhardness using computer vision methods. *Przeglad Elektrotechniczny* **99**, 323–329. https://doi.org/10.15199/48.2023.01.67 (2023).
43. Gonzalez, S. E. D. R. et al. A bibliometric analysis of circular economies through sustainable smart cities. *Sustainability* **15**, 15892. https://doi.org/10.3390/su152215892 (2023).
44. Reis, W. F., Barreto, C. G. & Capelari, M. G. M. Circular economy and solid waste management: Connections from a bibliometric analysis. *Sustainability* **15**, 15715. https://doi.org/10.3390/su152215715 (2023).
45. Mirzaie, S., Thuring, M. & Allacker, K. End-of-life modelling of buildings to support more informed decisions towards achieving circular economy targets. *Int. J. Life Cycle Assess* **25**(11), 2122–2139. https://doi.org/10.1007/s11367-020-01807-8 (2020).
46. Moncaster, A. M. & Song, J.-Y. A comparative review of existing data and methodologies for calculating embodied energy and carbon of buildings. *Int. J. Sustain. Build. Technol. Urb. Dev.* **3**(1), 26–36. https://doi.org/10.1080/2093761X.2012.673915 (2012).
47. Moncaster, A. M. & Symons, K. E. A method and tool for 'Cradle to Grave' embodied carbon and energy impacts of UK buildings in compliance with the new TC350 standards. *Energy Build.* **66**, 514–523. https://doi.org/10.1016/j.enbuild.2013.07.046 (2013).
48. Martínez, E., Nuñez, Y. & Sobaberas, E. End of life of buildings: Three alternatives, two scenarios. A case study. *Int. J. Life Cycle Assess* **18**(5), 1082–1088. https://doi.org/10.1007/s11367-013-0566-4 (2013).
49. Hawkins, D. & Mumovic, D. Evaluation of life cycle carbon impacts for higher education building redevelopment: A multiple case study approach. *Energy Build.* **150**, 507–515. https://doi.org/10.1016/j.enbuild.2017.05.058 (2017).
50. Delem, L. & Wastiels, L. The practical use of module d in a building case study: Assumptions, Limitations and Methodological Issues. *IOP Conf. Ser.: Earth Environ. Sci.* **323**(1), 012048. https://doi.org/10.1088/1755-1315/323/1/012048 (2019).
51. Qiu, Y., Dobbelaere, C. & Song, S. Energy cost analysis and operational range prediction based on medium- and heavy-duty electric vehicle real-world deployments across the united states. *World Electr. Veh. J.* **14**, 330. https://doi.org/10.3390/wevj14120330 (2023).
52. Imani, M. & Arabnia, H. R. Hyperparameter optimization and combined data sampling techniques in machine learning for customer churn prediction: A comparative analysis. *Technologies* **11**, 167. https://doi.org/10.3390/technologies11060167 (2023).
53. Yang, G., Zhang, J., Ma, Z. & Xu, W. Prediction of failure modes of steel tube-reinforced concrete shear walls using blending fusion model based on generative adversarial networks data augmentation. *Appl. Sci.* **13**, 12433. https://doi.org/10.3390/app132212433 (2023).
54. Azad, M. A. et al. A particle swarm optimization-adaptive weighted delay velocity-based fast-converging maximum power point tracking algorithm for solar PV generation system. *Sustainability* **15**, 15335. https://doi.org/10.3390/su152115335 (2023).
55. Ma, K. et al. Research on the efficiency of bridge crack detection by coupling deep learning frameworks with convolutional neural networks. *Sensors* **23**, 7272. https://doi.org/10.3390/s23167272 (2023).
56. Lin, Y.-H., Ting, Y.-H., Huang, Y.-C., Cheng, K.-L. & Jong, W.-R. Integration of deep learning for automatic recognition of 2D engineering drawings. *Machines* **11**, 802. https://doi.org/10.3390/machines11080802 (2023).
57. Andrade, C. B., Moura-Bueno, J. M., Comin, J. J. & Brunetto, G. Grape yield prediction models: Approaching different machine learning algorithms. *Horticulturae* **9**, 1294. https://doi.org/10.3390/horticulturae9121294 (2023).
58. Yang, W., Min, Z., Yang, M. & Yan, J. Energy poverty prediction and effective targeting for just transitions with machine learning. *Int. J. Environ. Res. Public Health* **128**, 107131. https://doi.org/10.1016/j.eneco.2023.107131 (2023).
59. Suzuki, A. et al. Structural damage detection technique of secondary building components using piezoelectric sensors. *Buildings* **13**, 2368. https://doi.org/10.3390/buildings13092368 (2023).
60. Christ, L., Milloch, E., Boshoff, M., Hypki, A. & Kuhlenkötter, B. Implementation of digital twin and real production system to address actual and future challenges in assembly technology. *Automation* **4**, 345–358. https://doi.org/10.3390/automation4040020 (2023).
61. Bodyanskiy, Y., Kulishova, N. & Chala, O. The extended multidimensional neo-fuzzy system and its fast learning in pattern recognition tasks. *Data* **3**, 63. https://doi.org/10.3390/data3040063 (2018).
62. Kiurchev, S. et al. Automated Control of the Gear Profile for the Gerotor Hydraulic Machine. Lecture Notes in Mechanical Engineering 32–43 (Springer International Publishing, Cham, 2022) https://doi.org/10.1007/978-3-031-16651-8_4.
63. Nazarova, O. et al. Mechatronic automatic control system of electropneumatic manipulator. *Sci. Rep.* **14**, 6970. https://doi.org/10.1038/s41598-024-56672-4 (2024).

64. Nazarova, O., Osadchyy, V., Shulzhenko, S., Olieinikov, M. Software and Hardware Complex for The Study of Electropneumatic Mechatronic Systems. In *2022 IEEE 4th International Conference on Modern Electrical and Energy System (MEES)* 1–6 (Kremenchuk, Ukraine, 2022) https://doi.org/10.1109/MEES58014.2022.10005698.
65. Dmytriv, V. T. et al. Study of the pressure regulator work with a spring-damper system applied to milking machine. *INMATEH – Agric. Eng.* **52**(2), 61–67 (2017).

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Declarations

Competing interests
The authors declare no competing interests.

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