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Prediction of optimum design of welded beam design via machine learning

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ABSTRACT

Design optimization is an important engineering design topic. One of the important issues in structural design is to minimize the cost. This study based on an engineering problem of Welded Beam Design aims to minimize the cost of the beam with machine learning (ML) models depending on the constraints on applied load, shear stress, bending stress and end deflection. The data set to be used in this context was created using a metaheuristic optimization algorithm. This hybrid algorithm is based on the classical Jaya algorithm by adding the student phase of Teaching Learning Based Optimization. The dataset obtained as a result of the optimization is a dataset with 1189 rows. Six different algorithms were used for prediction analyses. These are Linear Regression, Decision Tree, Elastic Net, K-Nearest Neighbour, Random Forest, and XGBoost algorithm. In the data set, load, length, and displacement are input; the design variables such as b, h, l, t and minimum cost are output. Since there is more than one output in the dataset, Multioutput Regression is applied. The performance of regression models was assessed using the Coefficient of Determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). According to the results obtained, the Decision Tree Model showed the best performance among the other models (R^2=1, MAE=6.13e-11, RMSE=9.47e-10).

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1. Introduction

Optimization is the process of finding the optimum solution to obtain the best value of the objective function. Structural optimization is a type of optimization in which the best of the available options in structural design is sought. There are many studies in the literature where structural optimization and machine learning (ML) are performed using algorithms. In engineering optimization, the problem is generally nonlinear because there are design variables and design constraints on the analysis results that require the design of all variables. In that case, a numerical optimization technique is used that uses iterations with randomly defined candidate solutions to try out the best result. Due to these factors, when an optimization problem cannot be solved using mathematical methods, a systematic methodology is required. This need can be achieved by employing metaheuristic techniques. In metaheuristic methods, the essential problem is formulated in an optimization phase that generates updated candidate design variables. Bekdaş and Nigdeli (2011) used Harmony search (HS) to obtain the optimum parameters of tuned mass dampers (TMD) used for structural control. Thus, more efficient structural control can be achieved with optimum parameter values. Bekdaş (2014) used the harmony search algorithm for the economic design of post-tensioned axisymmetric cylindrical reinforced concrete (RC) walls according to ACI 318. The results showed that the optimization performed with the HS algorithm was effective in the optimum design of the post-tensioned reinforced concrete walls considered in the study. Bekdaş et al. (2015) aimed to minimize the weight of truss structures using the flower pollination algorithm (FPA). The weight obtained with FPA was also optimized compared to other methods. Bekdaş and Nigdeli (2016) carried out

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the cost optimization of reinforced concrete elements considering the ACI 318 code by using the bat algorithm. The method used has shown effective success compared to other methods. Kayabekir et al. (2018) performed the optimum design of carbon fiber-reinforced polymer strips used to increase the shear capacity of a reinforced concrete beam using the Jaya algorithm. As a result, Jaya algorithm, which is easy to apply in terms of phase, has been successful in the optimization process. Ulusoy et al. (2019) optimized the proportional gain, integral time and derivative time, which are the optimum parameters of Proportional-Derivative-Integral (PID) type controllers for active control of structures, using the Teaching Learning-Based Optimization (TLBO) algorithm and achieved effective results. Ulusoy et al. (2020) used meta-heuristic algorithms such as Harmony Search, Bat Algorithm and Teaching Learning-Based Optimization for cost minimization of reinforced concrete beams and achieved optimum results.

In recent years, machine learning (ML) has emerged as a promising tool for tackling optimization problems. ML techniques offer the ability to learn patterns and relationships from data, enabling the estimation of complex functions without explicitly modeling them. This capability has led to the development of innovative approaches for estimating and solving optimization problems. Huang et al. (2012) undertook research focusing on hazard identification within smart buildings employing machine learning (ML) methods. They devised an ML algorithm capable of analyzing data gathered from sensors to autonomously issue timely warning alerts for identified hazards. The experimental findings confirmed the efficacy of the ML algorithm and demonstrated the benefits of employing a wireless sensor network for prompt hazard detection in buildings. Jeon et al. (2014) presented statistical models for the shear strength of column-beam connections using BC techniques. The multiple linear regression method was used in the study. It has been observed that this method is applicable for evaluating the joint zone capacity in existing frame-type reinforced concrete buildings. Doğan (2018) tried to determine the post-earthquake damage levels of reinforced concrete columns with a smart system-based method. Data sets were created with the help of 390 damaged images taken from column surfaces. The characteristics of the cracks were extracted from the damage images and the damage level of the columns was classified using ML classifier algorithms according to these data. The successes obtained from the predictions vary between 64% and 80%. Okazaki et al. (2020) conducted a study on the applicability of ML to crack modeling in concrete bridges. The results showed excellent applicability of ML even for very little data. Cao et al. (2020) used ML methods to estimate moments for column-beam connections. The accuracy of the predicted prediction was compared with Artificial Neural Networks and Genetic Programming (GP) and the results showed that ML algorithms provided better performance. Yücel et al. (2021) obtained data by optimization process to be used in machine learning for prediction in reinforced concrete elements. As a result, they achieved successful application. Cakiroglu et al. (2021) minimized the CO_2 emission and cost of steel tube columns filled with concrete. Thus, they optimally dimensioned the cross-sections of the columns. Yücel et al. (2021) estimated the optimum dimensions of reinforced concrete (RC) cantilever retaining walls using metaheuristic algorithms and artificial intelligence and machine learning methods. Successful results were obtained for estimation in the study. Bekdaş et al. (2022) estimated the wall thickness of a cylindrical water tank using HS optimization algorithm using a data set consisting of a large number of optimum design values. The ML models used in the study achieved high success in prediction. Bekdaş et al. (2022) generated data for the optimal sizing of reinforced concrete circular columns using the adaptive search algorithm and used it for prediction in machine learning. Thus, they established a highly efficient estimation procedure. Aydın et al. (2023a) used machine learning models to estimate the cooling load of buildings in hot locations. In the study, Histogram Gradient Boosting and Stacking models were used with high success. Aydın et al. (2023b) performed soil classification using machine learning. As a result of this study in which they processed the data with different processes, boosting models had high performance. Aydın et al. (2023c) applied meta-heuristic optimization algorithms and neural network models to minimize environmental damage in cement production. In the study, the hyperparameter optimization algorithm achieved the highest success with the genetic algorithm (GA). Aydin et al. (2024a) investigated the optimum TMD parameters with a new optimization algorithm, the Archimedes Optimization Algorithm (AOA). They compared AOA with the Jaya Algorithm (JA) and the Modified Jaya Algorithm (SJA), which were applied on the same problem and the results were obtained and AOA outperformed the other algorithms. Aydin et al. (2024b) modified the parameters of the algorithm to optimize the volume of the truss system with AOA. As a result, the effect of the parameters for minimum volume sizing of the truss system was investigated. Coşut et al. (2024) used T-shaped elements for area optimization according to the maximum stress value using Particle Swarm Optimization (PSO). Thus, they concluded with which stress value the minimum area is reached. Aydın et al. (2023d) used the Flower Pollination Algorithm (FPA) to minimize the cost of a reinforced concrete beam. Their analysis of cases with different algorithm parameter values showed that the use of random sp provides the best performance. Aydin et al. (2023) used Archimedes Optimization Algorithm (AOA), Teaching-Learning Based Optimization and Flower Pollination Algorithm to optimize the weight of a cantilever beam. The new algorithm AOA showed effective performance in this problem.

Design optimization stands as a pivotal topic in engineering, particularly in the realm of structural design where minimizing costs holds paramount importance. This study delves into the engineering conundrum of Welded Beam Design, aiming to curtail the beam's cost through the application of machine learning (ML) models, all while adhering to constraints on loading load, shear stress, bending stress, and end deflection. The dataset utilized in this endeavor was meticulously crafted using a metaheuristic optimization algorithm. This hybrid algorithm amalgamates the classical Jaya algorithm with the student phase of Teaching Learning Based Optimization (TLBO), furnishing a robust foundation for data generation. Six distinct algorithms were employed for predictive analyses: Linear Regression, Decision Tree, Elastic Net, K-Nearest Neighbour, Random Forest, and the XGBoost algorithm. Due to the presence of multiple outputs in the dataset, Multioutput Regression techniques were employed to ensure accurate modeling and prediction. In this study, both the optimum design of the welded beam has been realised and its optimum design has been predicted by machine learning models.

2. Methodology

2.1. Optimization

Optimization is the process of finding the best values for system parameters among all possible values to optimize the solution to a problem. Since optimization problems exist in every research field, it is necessary to develop optimization techniques (Yang 2010). Optimization aims to find the optimum value among the solutions. Each iteration represents the starting point for the next iteration. When optimization is applied structurally, it aims to find the design that provides cost minimization and the necessary structural requirements. The optimum design includes the most efficient combination of shape, size and topology values. Optimization methods have a certain design framework. Optimization results are required to remain within certain limits. The objective function in optimization is the definition of the value to be kept at minimum level as a function. The aim of optimization is to find the most suitable combination for these variables within the specified limits.

Due to the drawbacks of traditional optimization algorithms, such as being stuck in local optima and the need to specify the search space, interest in metaheuristic optimization approaches has increased in recent decades. When, examining the behaviors of organisms in nature, such as foraging, social behavior, and survival, we find that there are several intelligent approaches. When metaheuristic algorithms inspired by these approaches are created, they yield very good results in solving real-world problems (Fister et al. 2013). Metaheuristic algorithms are used to solve optimization problems and find optimal designs. Depending on the problem type, the objective function is minimized or maximized to produce an optimal design under existing constraints. Metaheuristics are heuristics that are inspired by nature. Metaheuristics aims to use the search space more efficiently by further improving methods. These are often preferred because they can solve large, complex problems. Especially in engineering, solving complex optimization problems is very important. Metaheuristic algorithms can converge to an optimal solution and produce effective solutions in a short time (Osman and Laporte 1996). Metaheuristic optimization algorithms are a type of optimization algorithm designed to solve complex optimization problems that are difficult or impossible to solve using traditional optimization techniques. They work by simulating natural or social processes such as evolution, swarm behaviour (Kennedy and Eberhart 1995) or a process to explore the solution space, finding optimal or near-optimal solutions. The data produced by optimization using metaheuristic algorithms can be used in machine learning. In this study, 1189 data were generated with the Jaya algorithm and used for training in machine learning. In the study, optimization was performed with a hybrid Jaya Algorithm (JA) by using MATLAB2018. The data produced by the optimization were used in machine learning.

2.2. Optimization framework

The Jaya algorithm (JA) outperforms other well-known optimization algorithms in various benchmark problems due to its simplicity and computational efficiency. The Jaya algorithm is a powerful optimization algorithm that shows great promise in solving a wide range of engineering design problems and is a good alternative to more complex and computationally time-consuming optimization techniques. Although JA was developed with a simple logic, it is a very successful algorithm in terms of reaching the optimum solution in a relatively short time.

JA is a single-phase metaheuristic algorithm that uses the worst (g^w) and best (g^*) solutions in a single equation formulation developed by Rao. As Sankrit's name means "victory", by using the best existing solution, the new solution approaches the best solution in the world, but by using the worst solution, we diverge from the worst solution, you can win with optimization (Rao 2016). The Jaya algorithm starts the optimization process with an initial population of randomly selected solutions. The initial solution is randomly generated as Eq. (1).

$$D_{i,j} = \text{rand}(D_1, D_2, \dots, D_n) \tag{1}$$

Next, potential solutions are produced to seek improved alternatives compared to the current solutions, as outlined in Eq. (2). During the candidate solution identification process, the value of each design variable in the relevant solution is adjusted, bringing it nearer to the optimal design within the population and farther from the least favorable design, based on their respective distances (Rao 2016).

$$X_{\text{new}} = X_{\text{old}} + \text{rand}()(g^* - X_{\text{old}}) - \text{rand}()(g^w - X_{\text{old}}) \tag{2}$$

In this formulation, X_{new} and X_{old} are the updated new and existing solutions, respectively. A new solution is generated using a random number between 0 and 1 (rand(0,1)).

Although JA is a single-phase, parameterless algorithm, it is easy to apply, but local optimization can be problematic for JA. Therefore, the second stage is provided by the student stage of TLBO. In this stage of TLBO, two randomly selected existing solutions (X_i and X_j) are used, as shown in Eq. (2). The equation changes depending on the value of the objective function ($f(x)$).

$$X_{\text{new}} = \begin{cases} X_{\text{old}} + \text{rand}()\left(X_i - X_j\right) \text{ if } F(X_i) > F\left(X_j\right) \\ X_{\text{old}} + \text{rand}()\left(X_j - X_i\right) \text{ if } F(X_i) < F\left(X_j\right) \end{cases} \tag{3}$$

2.3. Machine learning

Artificial intelligence (AI) is a sub-branch of computer science and has gained a place in academia and industry by enabling computers to behave intelligently. With the development of computer technologies, the desire to give computers the ability to establish relationships between data has led to the emergence of machine learning (ML). Machine learning can train itself with many data and develop new behaviours by using this training for other different conditions. While artificial intelligence is the ability of programs to learn and behave like humans, machine learning is an algorithm written for the same purpose. There are some concepts used for optimization that aim to improve the performance of model prediction. In recent years, researches have been studied in the field of structural design optimization and machine learning applications for predictive modeling (Cakiroglu et al. 2022, 2023a, 2023b; Bekdaş et al. 2023; Cakiroglu and Bekdaş 2023; Liu et al. 2024; Aydin et al. 2024a).

There are many machine learning algorithms based on the learning technique. After the data set is prepared, machine learning algorithms are run to analyse the data. Multiouput regression is performed with these algorithms. The machine learning algorithms are trained using the training data set and then the success of the algorithms is tested on the test data set. The machine learning algorithms used in the study are as follows: Within the scope of the study, 6 different machine learning regression methods including Linear Regression, Decision Tree, Elastic Net, K-Nearest Neighbour, Random Forest and XGBoost algorithms were used for prediction.

2.3.1. Multioutput Regression

Multiple output regression is a machine learning problem in which multiple outputs are predicted based on given inputs. Multiple output regression has a wide range of applications. For example Nguyen et al. (2023) used the multioutput regression to predict the strain and energy absorption capacity of ultra-high performance fibre reinforced concrete (UHPFRC) at the highest tensile stress. Aydın et al. (2023e) applied optimization and multioutput regression together for environmentally friendly reinforced concrete column design.

Increasing the number of outputs to be predicted in machine learning can cause complexity. Because the increase of ML models corresponding to the output may increase the processing lines in the computer. Therefore, in such cases, the Multioutput Regression model (Pedregosa et al. 2011) with accurate predictors selected in the trial and error phase is preferred. In this study, Multioutput Regression will be applied to different ML models and the best model will be determined. Thus, it will be possible to select the right models that can show the best performance in predicting targets using MORM. The dataset in this study has 5 outputs with 3 inputs. Six different predictors including Linear Regression, Decision Tree, Elastic Net, K-Nearest Neighbour, Random Forest and XGBoost algorithms are used. A brief introduction to these models is given in the rest of the paper. Fig. 1 shows the ML process of the study.

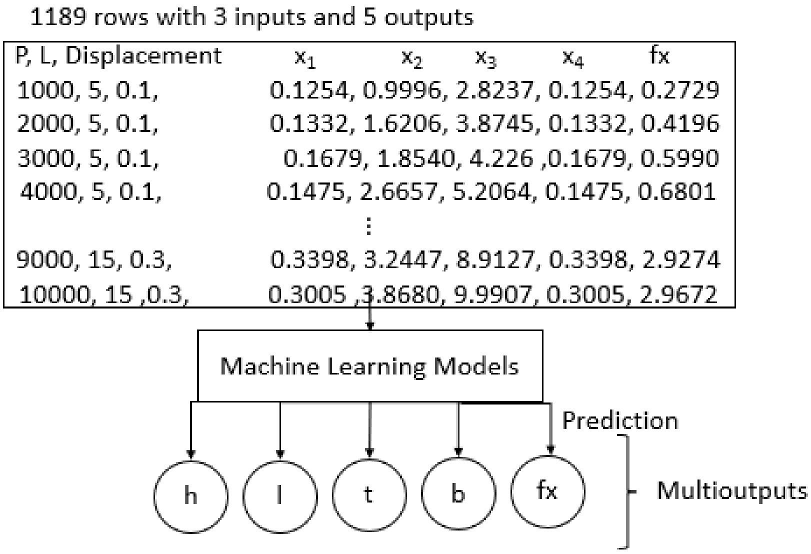

Fig. 1. Machine learning process.

2.3.2. Linear Regression (LR)

Linear regression is a statistical method that assumes a linear relationship between an input variable (x) and a single output variable (y). It seeks to model the relationship between the input and output by fitting a straight line to the observed data points. The linear regression model is characterized by its simplicity and interpretability, making it a popular choice for predicting continuous outcomes when the relationship between variables can be approximated by a straight line.

2.3.3. Decision Tree Regression (DTR)

A decision tree constructs a model for regression or classification represented in a tree-like structure. It iteratively divides the dataset into smaller subsets and builds associated decision trees incrementally. The resulting tree comprises decision nodes and leaf nodes. For soft classification, individual regression trees are constructed for each class. In this approach, the intensity values of pixels across various bands serve as predictor variables or feature vectors, while the known class proportions of the pixels, termed as soft reference data, are the target variables or target vectors for each regression tree. During prediction, intensity values are input into each regression tree, and the model provides estimated class proportions as the output. This process enables the assignment of soft classification probabilities to each class, offering more nuanced insights than traditional binary classification methods (Çene 2022).

2.3.4. ElasticNet Regression (ENT)

Elastic net regression is a variant of linear regression that incorporates a penalty term to adjust predictor coefficients. This penalty term combines both the L1 norm (absolute value) and L2 norm (squared) of the coefficients, weighted by a parameter known as alpha. By leveraging this combination, elastic net regression harnesses the advantages of both Lasso regression and Ridge regression. In essence, elastic net regression is adept at grouping and reducing parameters linked to normalized variables. It provides the flexibility to retain these parameters in the equation or remove them altogether, offering a versatile approach to model selection and feature reduction (Aytekin 2021).

2.3.5. K-Neighbors Regression (KNN)

In the context of regression, KNN is often referred to as "K-nearest neighbor regression" or "KNN regression." It is a simple and intuitive algorithm that makes predictions by finding the K data points closest to a given input and either averaging their target values (in the case of numerical regression) or choosing the majority class. In KNN regression, the distance between the selected observation and other observations is calculated first.

2.3.6. Random Forest Regression (RFR)

The Random Forest (RF) regression algorithm operates as an ensemble learning method, amalgamating a multitude of regression trees. Each regression tree encapsulates a series of conditions or constraints organized hierarchically and applied sequentially from the root to the leaves of the tree. The RF algorithm initiates by generating several bootstrap samples with replacements from the original training dataset. Subsequently, a regression tree is constructed for each bootstrap sample. At each node within every tree, a subset of input variables, randomly selected from the total set, is considered for binary splitting. This randomness injects diversity into the trees, enhancing the robustness and generalization capabilities of the overall ensemble model.

2.3.7. eXtreme Gradient Boosting (XGBoost)

XGBoost stands as a gradient-boosting-based decision tree ensemble meticulously engineered for high scalability. In line with gradient boosting, XGBoost iteratively builds an additive extension of the objective function by minimizing a specified loss function. Notably, XGBoost concentrates solely on decision trees as the fundamental classifier. To regulate the complexity of these trees, a tailored variation of the loss function is employed, ensuring optimal model performance while controlling for overfitting. This meticulous approach allows XGBoost to deliver superior scalability and efficiency in handling diverse datasets and modeling tasks.

2.4. Dataset

To be used in machine learning, a dataset of 1189 rows was obtained using the optimization process. Firstly, by using P, L and displacement values in the optimization performed on MATLAB, a dataset of 1189 rows with optimum size and optimum cost values was obtained. This dataset was used in machine learning. There are 3 inputs and 5 outputs in the data set. Inputs are P, L, and displacement. In the training data, the applied load (P) was taken between 500-10000 lb, length (L) was taken between 5-15 in and the displacement limit was taken as between 0.1-0.3 in. The outputs are h (x_1), l (x_2), t (x_3) and b (x_4) and the objective function, cost. Table 1 shows the statistical properties of the data set.

Table 1. Statistical properties of the data set.

Inputs and outputs	Mean	std deviation	min	max
P (lb)	5478.5534	2878.9704	1000	10000
L (in)	9.9798	3.1677	5.0	15.0
Displacement (in)	0.1997	0.0631	0.1	0.3
x_1 (in)	0.1940	0.0548	0.1250	0.4278
x_2 (in)	2.9981	1.0403	0.9805	5.8534
x_3 (in)	7.0081	1.8172	2.7888	10.0
x_4 (in)	0.1940	0.0548	0.1250	0.4278
f_x	1.3215	0.6628	0.2725	3.0546

From Table 1, the mean value, standard deviation, min and max value of inputs and outputs can be seen. Fig. 2 shows the scatter plot of the dataset. Thus, a comparative scatter between inputs and outputs is shown in each cell. In the diagonal, there are also histograms in which there will be no self-scattering.

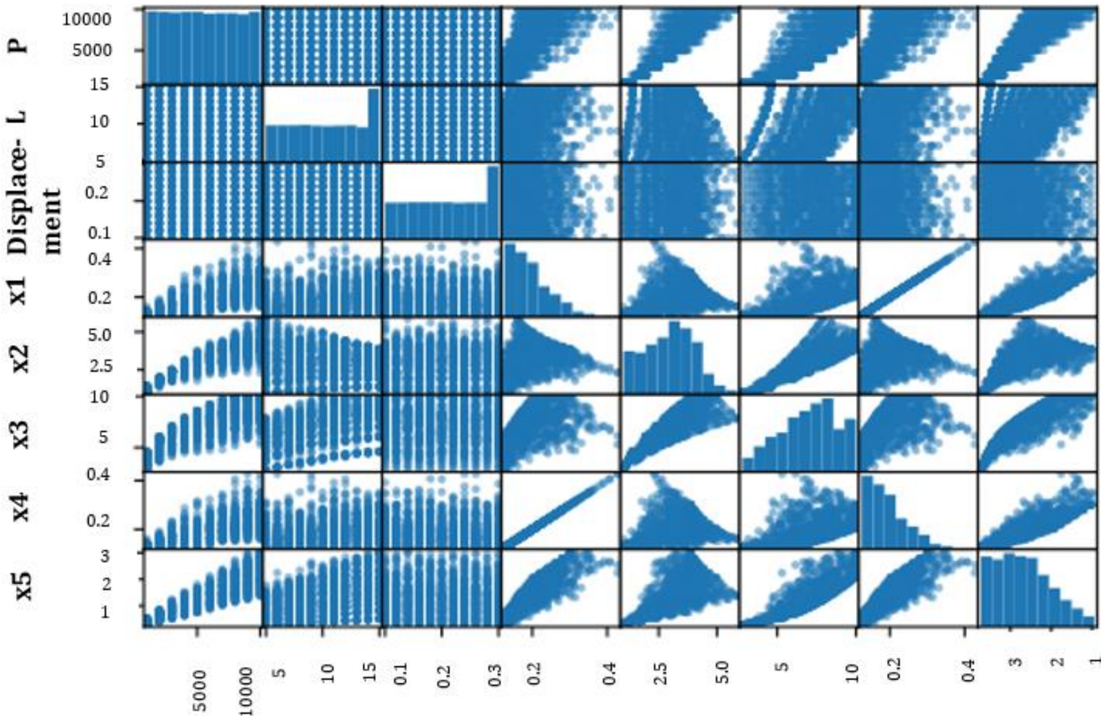

Fig. 2. Scatter plot of dataset.

From Fig. 3, the overall process of the study can be understood. As indicated by Fig. 3, firstly dataset was generated by Jaya Algorithm and achieved best (optimum) results. Then this dataset was used different predictive models and train test split used (30-70%). At the end, the best predictive model is determined.

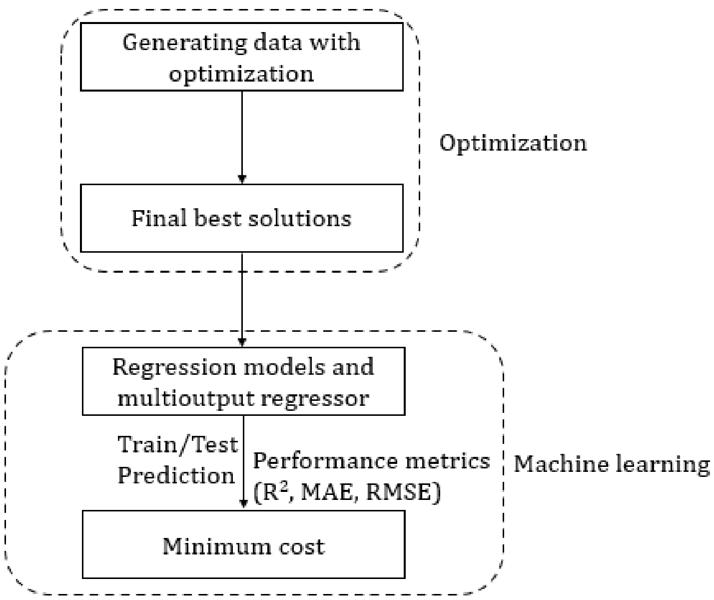

Fig. 3. General framework of the study.

3. The Welded Beam Problem

Welded beams are designed for structural support to withstand buckling under heavy loads. Welded Beams provide a superior durability performance where they are applied. Welded beams are available in a wide range of sizes, do not require preheating for welding, are prefabricated. It has applications in commercial and residential construction, mining and energy facilities, engineering, transport and many other fields. Fig. 4 shows a rigid member welded to a beam in a welded beam design. As can be seen in the figure, load is applied at the end of the member. The beam will be optimized for minimum cost by varying the weld and member dimensions. The design variables of the problem are shown in Fig. 4 (h (x_1), l (x_2), t (x_3) and b (x_4)).

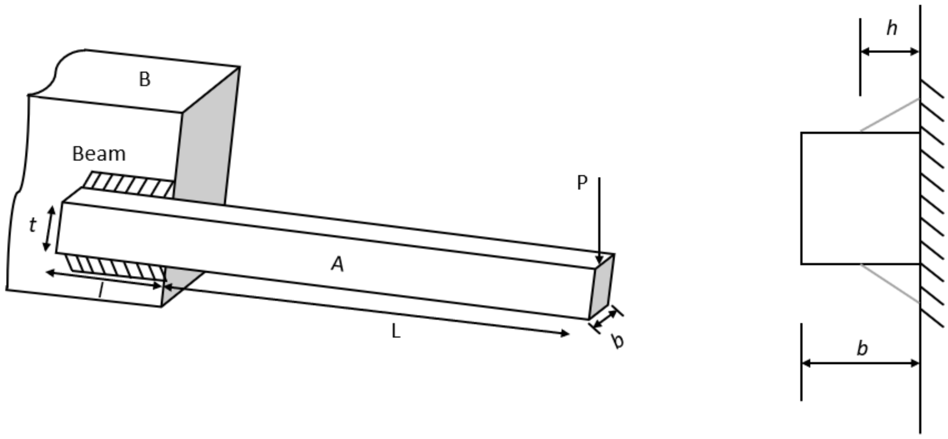

Fig. 4. Welded beam.

The aim of the study, which is to minimize the cost of the cantilever beam design problem, is formulated by Eq. (4).

$$\min(f(x)) = 1.10471{x_1}^2 x_2 + 0.04811 x_3 x_4 (14.0 + x_2) \quad (4)$$

The design constraints consist of shear stress limits (τ), bending stress (σ), buckling load (P_c) and end deflection (δ). The design constraints in the problem are given in Eqs. (5-11) (Savsani 2014).

$$g_1(\mathrm{x}) = \tau(\mathrm{x}) - \tau_{\max} \le 0 \quad (5)$$

$$g_2(\mathrm{x}) = \sigma(\mathrm{x}) - \sigma_{\max} \le 0 \quad (6)$$

$$g_3(\mathrm{x}) = x_1 - x_4 \le 0 \quad (7)$$

$$g_4(\mathrm{x}) = 0.10471{x_1}^2 + 0.048111 x_3 x_4((14.0 + x_2) - 5.0 \le 0 \quad (8)$$

$$g_5(\mathrm{x}) = 0.125 - x_1 \le 0 \quad (9)$$

$$g_6(\mathrm{x}) = \delta(\mathrm{x}) - \delta_{\max} \le 0 \quad (10)$$

$$g_7(\mathrm{x}) = \mathrm{P} - P_c \le 0 \quad (11)$$

The parameters required for the calculation of these constraints are given in Eqs. (12-20).

$$\tau(x) = \sqrt{(\tau')^2 + 2\tau'\tau''\frac{x_2}{2R} + (\tau'')^2} \quad (12)$$

$$\tau' = \frac{P}{\sqrt{2}x_1x_2} \quad (13)$$

$$\tau'' = \frac{MR}{J} \quad (14)$$

$$M = P\left(L + \frac{x_2}{2}\right) \quad (15)$$

$$R = \sqrt{\frac{x_2}{4} + \left(\frac{x_1+x_3}{2}\right)^2} \quad (16)$$

$$J = 2\left[\sqrt{2}x_1x_2\left\{\frac{x_2^2}{12} + \left(\frac{x_1+x_3}{2}\right)^2\right\}\right] \quad (17)$$

$$\sigma(x) = \frac{6PL}{x_4x_3^2} \quad (18)$$

$$\delta(x) = \frac{6PL^3}{Ex_4x_3^3} \quad (19)$$

$$P_c(x) = \frac{4.013E\sqrt{\frac{x_3^2x_4^6}{36}}}{L^2}\left(1 - \frac{x_3}{2L}\sqrt{\frac{E}{4G}}\right) \quad (20)$$

Here E=30·10^6 psi, G = 12·10^6 psi, $\tau_{\max}$= 13600 psi, $\sigma_{\max}$=30000 psi. With the first constraint (g_1), it is ensured that the maximum shear stress developed is less than the safe shear stress of the weld material. With the second constraint (g_2), it is checked whether the maximum normal stress developed is less than the safe normal stress in the beam. The third to fifth constraints (g_3 - g_5) ensure that the geometric dimensions are suitable for design. The sixth constraint (g_6) ensures the displacement limit of the beam. The seventh constraint (g_7) ensures that the load on the beam is not greater than the safe buckling load. In the equations, M is the moment, P is the force on the beam and P_c is the buckling load on the bar (Akyol and Feneaker 2022).

4. Results and Discussion

The performance of regression models was assessed using key metrics such as the Coefficient of Determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). R^2 quantifies the proportion of variability in the dependent variable explained by the model. MAE represents the average magnitude of prediction errors, while RMSE provides a measure of the typical magnitude of these errors. While individual results may not offer substantial insights, they serve as numerical benchmarks for comparing different model performances, aiding in the selection of the most suitable regression model. RMSE is derived from the square root of MSE, where MSE quantifies the average squared difference between predicted and actual values. MAE, on the other hand, calculates the average of all absolute prediction errors. Performance metrics for the machine learning models employed in this study are presented in Table 2.

Table 2. Performance metrics of ML models.

Model	R^2	MAE	RMSE
Linear Regression	0.7550	0.2318	0.2886
Decision Tree Regressor	1.0	6.1344e-11	9.4637e-10
Elastic Net Regressor	0.6951	0.2432	0.3089
K Neighbors Regressor	0.8359	0.1343	0.1999
Random Forest Regressor	0.9647	0.0604	0.0935
XGBoost	0.9660	0.0611	0.0860

According to the results in the Table 2, the R^2 value of the Decision Tree is 1. This value was obtained as 0.7550, 0.6951, 0.8359, 0.9647 and 0.9660 with Linear Regression, ElasticNet, KNN, RFR and XGBoost algorithms respectively. As a result of the analysis, DTR showed both the fastest and the most successful performance for minimum cost prediction. Decision Tree was the most successful ML model in predicting the values to minimize the cost. It has the highest R^2 and the lowest error values. It is followed by XGBoost, which is very close to Random Forest. Linear Regression performed the worst with the lowest R^2 and the highest error values.

5. Conclusions

In structural design, economy is an indispensable element as long as it does not harm reliability. Nowadays, very large amounts of data can be accessed using optimization. With the ability to generate data using optimization and the development of machine learning methods that can process the data, it is possible to reduce costs in structural engineering design. The main objective of this study is to apply machine learning algorithms to engineering design and to realize less costly design. For this purpose, load, length and displacement were determined as input and b, h, l, t, minimum cost were determined as output. By using these input and output data, Linear Regression, Decision Tree, Elastic Net, K-Nearest Neighbour, Random Forest, and XGBoost algorithms, the result that will give the minimum cost of the welded beam is reached.

In this research, optimization and machine learning are performed together. The performance of ML models were compared using Python. Based on the comparison of these results, Decision Tree Regression was superior (R^2=1, MAE=6.13e-11, RMSE=9.47e-10) to other ML models for the prediction of minimum cost design. In summary, this study demonstrates that optimization and ML models could be used effectively to design with minimum cost.

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Conflict of Interest

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Author Contributions

All of the authors made substantial contributions to conception and design, or acquisition of data, or analysis and interpretation of data; were involved in drafting the manuscript or revising it critically for important intellectual content; and gave final approval of the version to be published.

Data Availability

The datasets created and/or analyzed during the current study are not publicly available, but are available from the corresponding author upon reasonable request.

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