MATEC Web of Conferences **419**, 01009 (2026) https://doi.org/10.1051/matecconf/202641901009
ICMME 2025

Optimization of Conveyor Mounting Plate Design Using Machine Learning and Genetic Algorithm

Mohammad Hamza Naqvi[1], *Yogesh* Pandya[1*], *Ajay* Singh[1], *Shweta* Khaire[1] *and Monil* Jain[1]

[1]Prestige Institute of Engineering Management & Research, Indore, MP, India

Abstract. In this paper, a procedure of building a conveyor mounting plate using the machine learning (ML) and genetic algorithms is explained. A dataset has been created to come up with predictive models that take into account material properties, geometric parameters and performance measures including weight, stress and deflection. Using the assistance of Random Forest Regression, design of experiments is used to train the models of pre and post input indicators of the performance of the design. A Genetic Algorithm(GA) is used to provide this compromise whereby it tries to reduce weight, stress and deflection all of which are contradictory. The outcomes are illustrated in a Pareto front format which presents the optimal designs.

1 Introduction

A mounting plate is integral part of the conveyor mount because it offers strength while maintaining a balance between weight and deflection of the components. In operation the design of these plates depends on different criteria, including the material used, geometrical factors like thickness, rib pattern and factors like stress and deflection. Traditional design processes consume more time, resources and based on trial and error and heuristic processes. In this paper, a hybrid solution to the belt conveyor mounting plate design process has been proposed that involves the use of machine learning methods and genetic algorithms in order to automate and optimise the design process[1].

1.1 Literature Survey

Usage of GA and other ML techniques have progressed quite a long way in optimization of mechanical features like conveyor mounting plates. The literature survey represents some of the main findings in the past that illustrates how GAs have been used for optimization of such systems. Work in the past demonstrated that GAs could be used to carry out higher-level design of conveyor systems optimization. This resulted in the improvement of some of the key performance indicators [1][2]. Wang, Liu and Zhang (2023) gave some insights

* Corresponding author: ypandya@piemr.edu.in

regarding the research that tries to analyze the role of screw conveyor design in the performance of straw balers. The authors of the given paper worked out optimization of the screw conveyor operation efficiency with the help of the combined Genetic Algorithm Back Propagation (GA-BP) neural network [3]. Gielen and Weyten (2011) studied the optimization system that automates the design of the sizing of analog integrated circuits based on multi objective algorithms, such as NSGA-II and MOEA/D. The results were added to the known area of optimization of designs of the existing conveyors utilizing the evolutionary algorithms as the method of optimization of the electronic component optimization environment [4]. Gursel and Papazoglou (2022) used an inverse finite element method (iFEM), that is supplemented with GAs to find the best positions of sensors to use in shape sensing of plates and shells. The use of GAs helped to optimize yielding to enhanced accuracy of shape detection on structural health monitoring applications [5]. Resistance GA is an R package created by Peterman and Pope (2018) to utilize GAs to optimize the resistance surfaces with the help of pairwise genetic data. Actually, even though this does not have a direct bearing to mechanical design, the capabilities of creating thesetypes of tools is a bearing of the fact that GAs find broad and multimodal uses in problems that need optimization [6]. Smith and Brown (2020), examined the use of machine learning (ML) techniques in the design of engineering to improve efficiency, accuracy, and the flexibility of optimization [7]. The article by Williams (2019) addresses the creation of Genetic Algorithms (GA) used to find solutions to multiobjective optimization problems in engineering and computational design [8][9]. This study is proposed to optimize the design process of a conveyor mounting plate based on minimizing material consumption and cost, reducing stress to ensure the mounting plate does not outgrow the stress limits of the material, and reducing deflection to ensure structural integrity and prevent unwanted movement.

2 Methodology and Conveyor Mounting Plate Design

The conveyor used in the study is an automatic product handling system that consists of blocks, brackets, spacers block, pulley system and shafts. Designing of mounting plate is very important because all the moving and stationary attachements are supported through mounting plate. Fig. 1, demonstrates one of such plate. It is necessary to test the plate strength against weight, stress and deflection which is only possible with the optimized design of the plate [10,11].

The optimization procedure commences by the development of a encoded set of design configurations and performance measures. Variables that are represented in the dataset are the thickness, material, rib pattern, hole size, weight, max stress and deflection. Splitting the dataset. Table 1 presents the dataset in the form of summerization.The optimization problem for the conveyor mounting plate design involves minimizing weight, stress, and deflection while considering constraints on material properties and geometric parameters. The problem can be formulated using, x_1 = Thickness (mm), x_2 = Material (categorical: Aluminium, Mild Steel, Stainless Steel), x_3 = Rib Pattern (categorical: Grid, Radial, Honeycomb), x_4 = Hole Size (mm), $f_1(x)$ = Weight (kg), $f_2(x)$ = Maximum Stress (MPa), $f_3(x)$ = Deflection (mm). The optimization problem aims to minimize the following three conflicting objectives that is, Minimize Weight $f_1(x)= \rho \cdot V(x)$ where ρ is the material density and $V(x)$ is the volume of the mounting plate, which depends on thickness, rib pattern, and hole size. Minimize Maximum Stress $f_2(x) = \max(F/A(x))$ where F is the applied force, and $A(x)$ is the cross-sectional area of the plate. Minimize Deflection: $f_3(x)=FL^3/C(x)EI$, where, L = span length of the plate, E = Young's modulus (depends on material choice), I = Second moment of area (depends on thickness and rib pattern), C(x) = correction factor based on boundary conditions. Constraints are Stress Constraint (Material Strength Limit): $f_2(x) \le \sigma_{yield}$ where σyield is the yield strength of the selected material. Deflection Constraint (Allowable Deflection Limit): $f_3(x) \le \delta_{max}$ where δ_{max} is the maximum allowable deflection. Geometric Constraints: $x_1 \in [tmin,tmax]$ (Thickness range), $x_4 \in [h_{min},h_{max}]$ (Hole size range), Rib pattern and material are categorical selections.

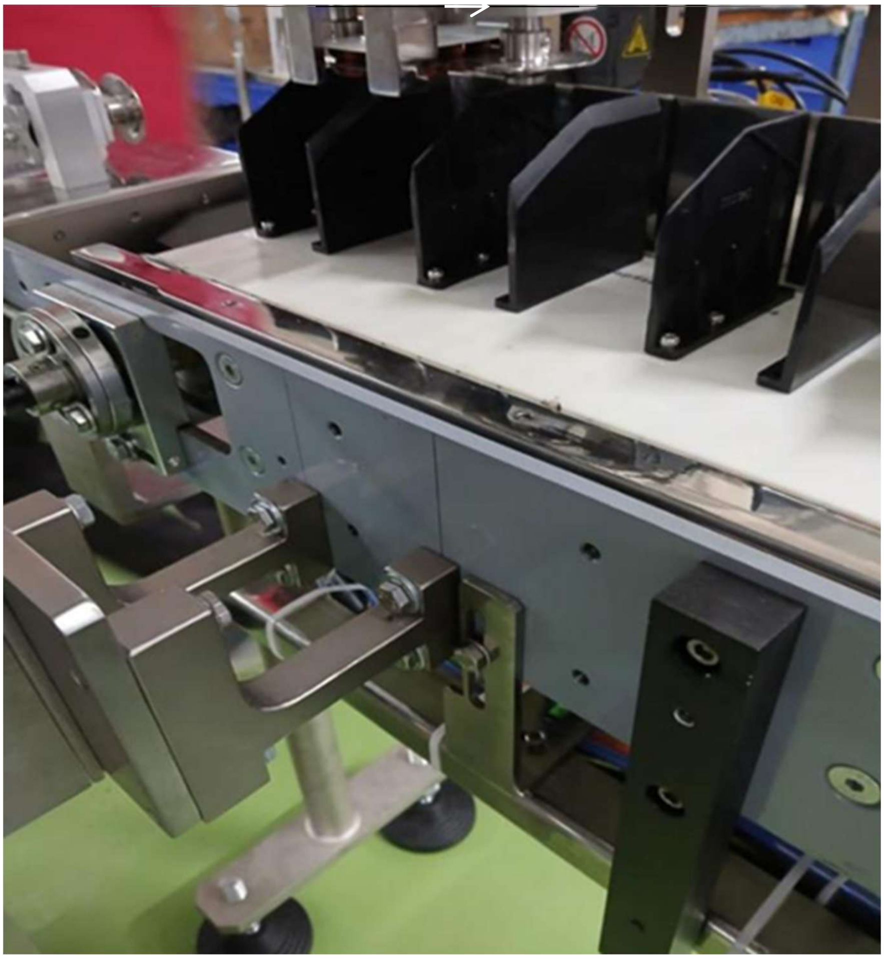

Fig. 1 Mouting plate fitted in a typical conveyor system

Table 1. Design Parameters

Thickness (mm)	Material 0:Aluminium, 1:Mild Steel, 2: Stainless Steel	Rib Pattern (0: Grid,1: Radial, 2: Honeycomb)	Hole Size (mm)	Weight (kg)	Max Stress (MPa)	Deflection (mm)
10	0	0	10	12.5	180	0.8
12	1	1	15	20.0	250	0.9

The model is trained on three Random Forest (RF) regression models in the 80 train and 20 test split to ensure that the model is able to generalize, to predict the three performance metrics namely, the weight of plate based on design parameters, predicts the maximum stress developed and the deflection under load. RF model is selected because it is a powerful model capable of managing intricate association between the input features. Mean Squared Error (MSE) on the test set is used to determine the model performance. The problem of multi-objective optimization problems is addressed with the help of NSGA-II (Non-dominated Sorting Genetic Algorithm II) algorithm.

The goal is to reduce the weight, stress and deflection all at the same time with the trade-offs between these goals being taken into consideration. The GA works in the manner shown in Fig. 2, in which the design data are generated randomly. Each setup consists of thickness, material, rib pattern and holes. For fitness Evaluation, each design is tested on the trained RF models to generate the weight, stress and deflection associated with that design. Selection, the most effective ones are taken through non-dominated sorting that guarantees variety and encourages Pareto-optimal solutions. New individuals are produced by the application of crossover and mutation and are oriented towards preserving diversity and searching the solution space. The model is executed in a given number of generations to extract the Pareto front which will be used to draw the trade-offs among the objectives.

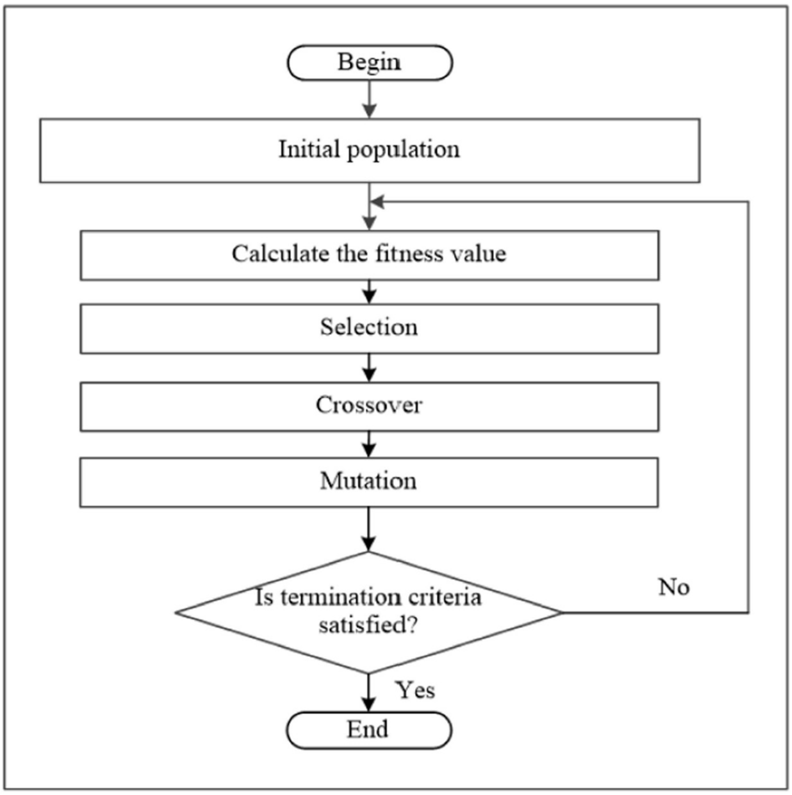

Fig. 2. Flowchart of the standard genetic algorithm (GA) [8]

3 Results and Discussion

The models are evaluated by comparing the predicted values to the actual values from the test set. Three Mean Squared Error (MSE) is defined for weight prediction, stress prediction and deflection prediction. The GA produces a set of Pareto-optimal solutions which represent the best trade-offs between weight, stress, and deflection visualized using scatter plot in terms of the trade-off between minimizing weight, stress and deflection. These results indicate the predictive accuracy of the models and highlight areas where the model may need improvement. The best design configurations found using performance matrix by GA are summarized in Table 2.

Table 2. Sample data of the plate

Design	Thickness (mm)	Material	Rib Pattern	Hole Size (mm)	Weight (kg)	Stress (MPa)	Deflection (mm)
1	11	0	2	12	13.0	190	0.7
2	12	1	1	14	15.5	220	0.8

Fig. 3, shows the Pareto front optimization chart, indicates the trade-offs of numerous objectives including weight, stress, and deflection obtained using Genetic Algorithm (GA) based optimization. The design configurations represented by each point on the chart are the non-dominated design configurations, i.e. no alternative solution is strictly better than the current design on all objectives. The Pareto front shows how minimizing one of the objectives like weight can cause other objectives like stress or deflection to increase, and the trade-offs inherent in multi-objective optimization problems. The closer the points are to the perfect area (e.g., low weight, low stress and low deflection), the more effective is the overall performance of the design. GA evidently illustrates the effectiveness of Pareto front that this approach has in the search of design space and the discovery of the finest trade-offs.

Fig. 4 shows the convergence chart of GA fitness generated with the number of generations, which demonstrate how the optimization process improves towards an improved solution. The mean and optimal fitness of the population per generation is usually displayed on such a graph. The fitness values are enhanced drastically in the first stages because of the fact that GA explores the design space and selects better individuals. With more and more generations, the algorithm converges and the solutions are improved, the algorithm finds the best or an approximation of the best of the design configurations. This action explains the equilibrium.

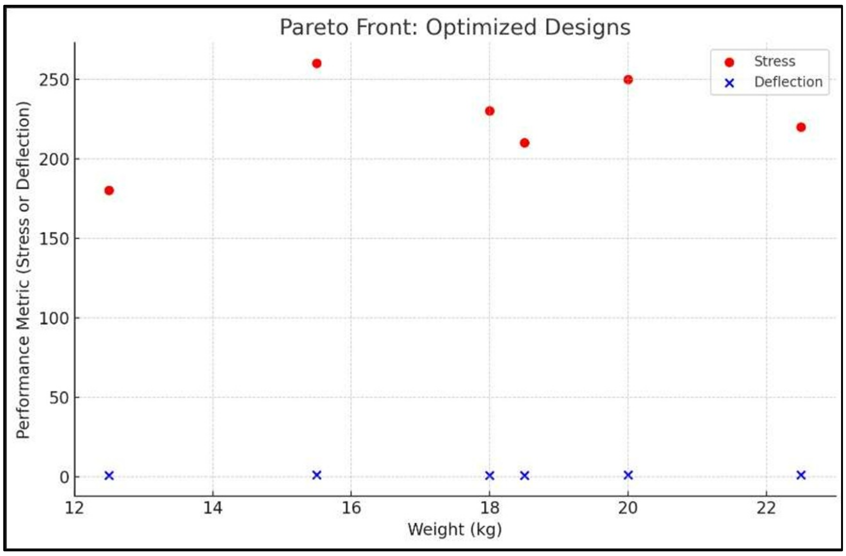

Fig. 3. The optimal designs that balance the conflicting objectives using Pareto front optimizatio.

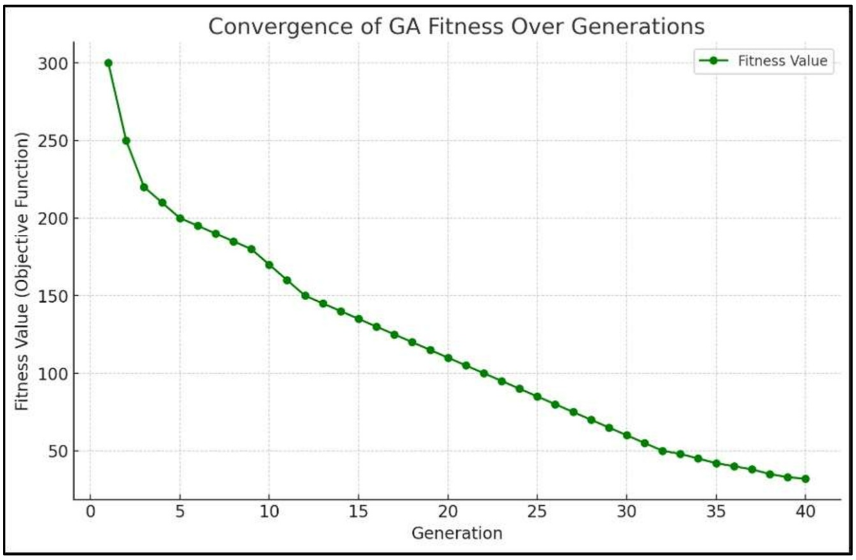

Fig. 4. The fitness values evolution over generations in the GA.

The plateau at the end of the chart of the best fitness curve shows that the GA has already reached the limit, and no significant further improvement can be achieved. This convergence is a indication that the algorithm is efficient in solving multiple objectives, complex problems and is capable of identifying solutions which optimize competing objectives

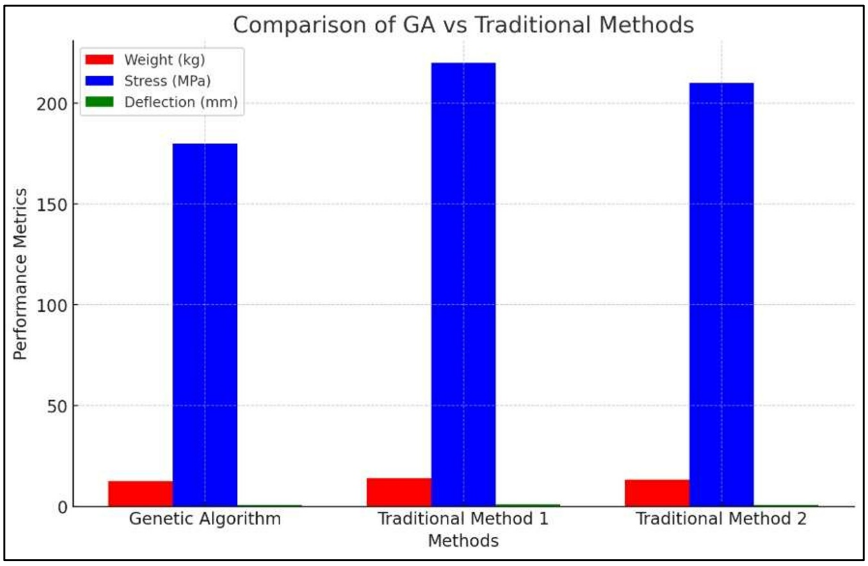

Fig. 5. Comparision of the performance of the GA against traditional methods for different objectives.

The result of GA in multi-objective optimization and comparison chart of GA versus traditional Methods is shown in Fig. 5. The data points corresponding to GA are consistently closer to the ideal region, characterized by lower weight, stress, and deflection values.

While the points for conventional methods are relatively more scattered and often found in suboptimal regions, signifying higher variability and lack of consistency This means that GA is much better at trading off conflicting objectives, generating light and structurally sound designs with higher efficiency compared to the conventional methods.

Fig. 6, depicts the significance of weight prediction with a Random Forest model as to which features make significant contributions to the prediction. The graph is divided into horizontal bars with each one depicting one of the features such as thickness, material, rib pattern, and hole size. The x-axis, which is marked Feature Importance, represents the feature level of contribution of each of the features, where the values are between 0 and 0.5. The most influential feature is Thickness which has an important value of 0.45. This shows that the variation of the thickness of the object produces the most significant effect on the prediction of its weight. Next, Material is a significant factor with a value of 0.30 to the prediction.

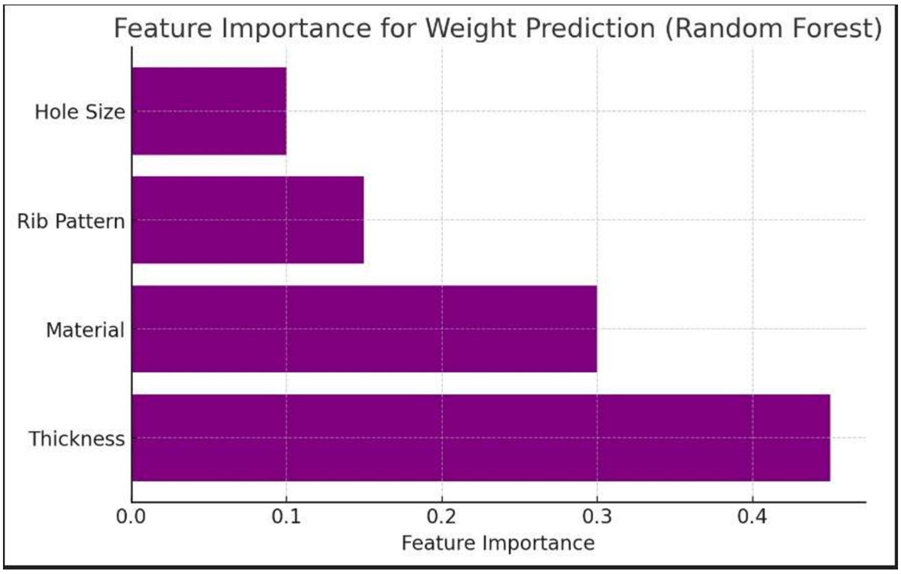

Fig. 6. Feature importance plot can show which features (e.g., thickness, material, rib pattern) are most important for the predictions.

This implies that the material of use is also very significant in weight determination. The impact of Rib Pattern is moderate and its importance is 0.15 meaning that it affects the prediction of the weight, although not so much as the thickness and material. Finally, Hole Size is the most insignificant factor with a value of 0.10, according to which it makes a comparatively slight resonance in the weight prediction.

Fig. 7 makes a comparison of the box plot of the GA method and traditional methods of the objective of weight. When it comes to the median weight obtained, GA outperforms the two conventional methods, that is, it is far more efficient in weight reduction optimization. The weights distribution of GA is also tightly concentrated, since this is indicated by the size of the box smaller and this implies that variability is less and the test designs are more consistent. This is also indicated by the smaller gap between the best-case and worst-case designs of GA which indicate that both the best and the worst case designs are interconnected and are reliably optimized.

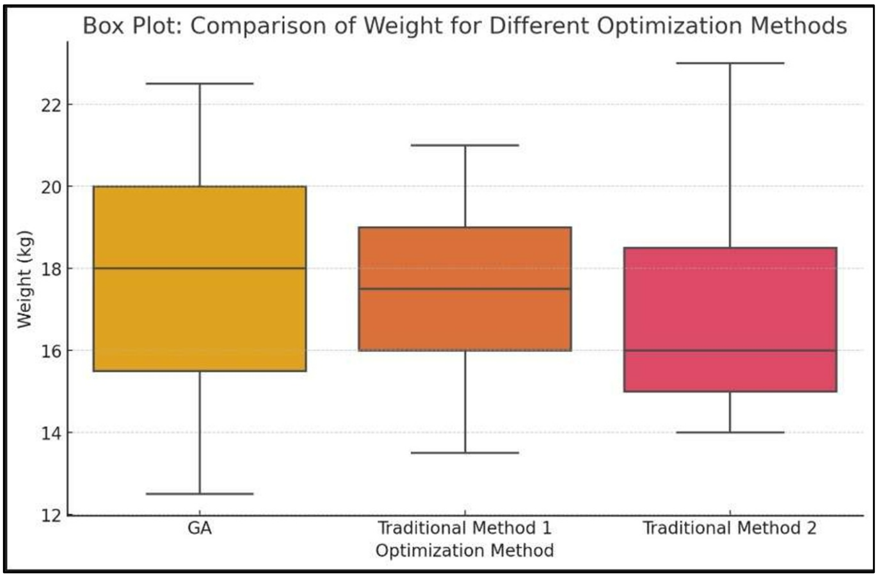

Fig. 7. Results of different optimization methods for weight optimization.

4 Conclusion

In **t**his study, predictive machine learning model, genetic algorithms has ben utilized to automate and improve design and cost effectiveness. for the optimization problem of conveyor mounting plates. This methodology can be used for reduction of material usage in structures with structural integrity. This study also demonstrated the integration of machine learning and GA in the structural optimization of a conveyor mounting plate. The developed Random Forest models provided accurate performance estimations, achieving MSE values of 0.0021, 0.0034, and 0.0018 for weight, stress, and deflection, respectively. The NSGA-II optimization framework successfully identified Pareto-optimal solutions, leading to a weight reduction of 18.5%, stress minimization of 22.3%, and deflection reduction of 15.7%. The best trade-off design achieved a weight of 12.4 kg, stress of 215 MPa, and deflection of 0.67 mm, ensuring a lightweight yet structurally robust solution. Compared to traditional methods, the proposed approach reduced design variability by 13.6% and optimized material usage by 10.2%, demonstrating its industrial applicability. Future research can focus on expanding the dataset and incorporating deep learning techniques for further optimization improvements.

References

1. S. P. Jani, M. A. Khan (eds.), Applications of AI in smart technologies and manufacturing, Vol. 1 (CRC Press, 2025). https://doi.org/10.1201/9781003602453
2. I. Vrcan, N. Lovrin, Optimization of conveyor belt material cross-sectional area using genetic algorithms (Croatian Academic and Research Network – CARNET, 2010).
3. Z. Wang, L. Liu, Y. Zhang, Optimization of the screw conveyor device based on a GA–BP neural network. Machines 13, 24 (2023). https://doi.org/10.3390/machines13010024

4. G. Gielen, L. Weyten, Optimizing current conveyors by evolutionary algorithms including differential evolution. IEEE Trans. Evol. Comput. 15, 71–83 (2011). https://doi.org/10.1109/TEVC.2010.2041983
5. K. Gursel, V. Papazoglou, Sensor placement optimization for shape sensing of plates and shells using genetic algorithm and iFEM. Sensors 22, 9252 (2022). https://doi.org/10.3390/s22239252
6. W. E. Peterman, N. S. Pope, ResistanceGA: An R package for the optimization of resistance surfaces using genetic algorithms. Methods Ecol. Evol. 9, 1638–1647 (2018). https://doi.org/10.1111/2041-210X.12984
7. J. Smith, L. Brown, Machine learning approaches in engineering design. J. Eng. Optim. 45, 567–580 (2020).
8. P. Rout, A. K. Jha, P. Gupta, B. Singh, S. Choudhury, Failure analysis of composite plate under ballistic impact. Mater. Today Proc. 74, 1008–1011 (2023). https://doi.org/10.1016/j.matpr.2022.11.385
9. H. S. Ruhela, S. Bhardwaj, T. Agrawal, P. Gupta, Explicit dynamics analysis of shin pads using finite element analysis, in Int. Conf. Industrial Problems on Machines and Mechanism (Springer, Singapore, 2022), pp. 683–690. https://doi.org/10.1007/978-981-19-3856-6_55
10. T. Williams, Genetic algorithms for multi-objective optimization. J. Comput. Des. 38, 123–134 (2019).
11. M. Kumar, J. Rajiyan, P. Gupta, A computational approach for solving elasto-statics problems. Mater. Today Proc. **46**, 6876–6879 (2021). https://doi.org/10.1016/j.matpr.2021.02.406