Optimal Design of a Cantilever I-Beam: A Response Surface Approach Using ANSYS Software

Optimisation plays a central role in modern engineering design and analysis. This paper presents a student-oriented example of multi-objective structural optimisation—the optimal design of a cantilever I-beam—to demonstrate how theoretical optimisation concepts can be combined with computational simulation. The study first introduces the fundamentals of optimisation theory, including objective functions, constraints, and the types of optimisation problems. Analytical and simulation-based approaches are briefly discussed. Subsequently, a response surface methodology (RSM) framework implemented in ANSYS Workbench is described to solve the problem of minimising simultaneously both the mass and the deflection of a cantilever I-beam. The approach integrates finite element analysis (FEA), design of experiments (DOE), and multi-objective optimisation to produce a Pareto front. This integrated workflow enhances engineering students' understanding of optimisation principles through hands-on simulation-based learning.

Introduction

Optimisation has become a cornerstone of modern engineering design and analysis, driving innovation across mechanical, civil, and aerospace applications. In a modern engineering context where engineering decisions must simultaneously address performance, sustainability, and cost efficiency, optimisation methods provide a formal mathematical framework to determine the most effective combination of design parameters (Papalambros 2002; Martins and Ning 2021). Whether it is minimising the mass of a structural component, maximising the aerodynamic performance of a wing, or reducing the thermal losses in an energy system, optimisation enables engineers to convert design trade-offs into quantifiable, reproducible, and transparent decision processes (Nemati et al. 2020, 2021; Nemati et al. 2022).

In contemporary industry, structural optimisation— particularly of beams, trusses, and shells—plays a vital role in light-weighting strategies and sustainable product development (Zingoni 2025). The ability to design safe yet material-efficient structures has a direct impact on both energy consumption and carbon footprint throughout a product's life cycle. Multi-objective optimisation frameworks allow simultaneous consideration of conflicting goals such as strength, stiffness, and cost, yielding a Pareto-optimal set of trade-off solutions rather than a single design point (De Weer et al. 2023). Among such applications, the cantilever I-beam represents a classic yet highly illustrative benchmark problem. Despite its apparent simplicity, it encompasses the essential elements of structural design: geometric parameterisation, load–deformation response, stress limitations, and manufacturability constraints (Moghimi et al. 2017; Moghimi and Ahmadi 2018; Kadivar et al. 2019).

From an educational perspective, introducing optimisation through a tangible structural problem provides students with a powerful way to bridge

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theory and practice. According to Reith *et al.* (Reith et al. 2024), successful engineering education requires the seamless integration of mathematical theory, computational modelling, and simulation-based experimentation. Their Web-Enhanced Learning Material (WELM) framework demonstrates that combining textbook knowledge with interactive numerical tools increases student motivation and fosters deeper conceptual understanding. Building on this approach, the present study adopts a student-centred methodology where learners not only derive equations analytically but also implement, simulate, and evaluate designs in a professional Computer-Aided Engineering (CAE) environment—specifically, ANSYS Workbench (Lee 2019).

The incorporation of commercial simulation platforms into teaching serves two pedagogical goals. First, it familiarises students with industry-standard workflows, improving employability and technical readiness (Friesel et al. 2022). Second, it shifts learning from abstract mathematics to problem-based inquiry, consistent with constructivist principles in engineering education (Neumann 2013; Donnelly and Fitzmaurice 2005). By coupling theoretical optimisation formulations with finite-element analysis (FEA) inside ANSYS, students can visualise how design variables influence stress distribution, deformation, and overall structural performance. The graphical and parametric capabilities of the software transform optimisation from a purely numerical exercise into an intuitive exploration of design trade-offs.

The growing availability of optimisation modules within CAE packages has further popularised advanced methods such as response surface methodology (RSM). RSM provides a statistics-based surrogate model that approximates the relationship between input variables and system responses (Montgomery 2023). Rather than performing thousands of expensive FEA simulations, RSM constructs polynomial or Kriging surfaces from a limited Design of Experiments (DOE) dataset. Once trained, these surrogate models allow engineers to predict performance, identify sensitivities, and execute multi-objective searches in a fraction of the computational time. For educational purposes, RSM offers an accessible and visual introduction to the concepts of design space exploration, approximation error, and optimisation convergence (Montgomery 2023).

Integrating RSM with ANSYS DesignXplorer enables a complete optimisation workflow: parameterisation of the geometry, automatic DOE sampling and surrogate-surface construction. Through this workflow, students can perform both analytical modelling—by deriving beam deflection and stress equations—and simulation-based optimisation, linking theoretical equations to numerical results. The activity directly supports higher-order cognitive objectives such as analysis, evaluation, and synthesis as defined by Bloom's taxonomy (Forehand 2010).

This paper therefore presents the optimal design of a cantilever I-beam as an educational case study that combines the fundamental concepts of optimisation with practical computational implementation. The objectives of the study are threefold: (1) to introduce undergraduate engineering students to the mathematical structure of single- and multi-objective optimisation problems, including the formulation of objective functions, constraints, and design

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variables; (2) to demonstrate the use of response surface methodology as a surrogate-based technique for reducing computational cost while maintaining high accuracy; and (3) to show how the complete optimisation process can be implemented within ANSYS Workbench, providing a realistic professional workflow for structural design.

The remainder of the paper is structured as follows. Section II reviews the fundamentals of optimisation, including linear, nonlinear, and multicriteria formulations. Section III outlines common solution methods, contrasting analytical approaches with numerical and metaheuristic techniques. Section IV formulates the cantilever I-beam problem and presents its governing equations and constraints. Section V details the response surface methodology and its implementation in ANSYS Workbench, while Section VI discusses results and educational outcomes. Finally, Section VII summarises conclusions and recommendations for integrating optimisation exercises into engineering curricula.

By integrating optimisation within an authentic simulation context, this study contributes to the growing movement in engineering education that emphasises experiential and computation-integrated learning. The proposed framework does not require students to become expert programmers or mathematicians but equips them with the ability to judge the quality of models, interpret optimisation outcomes, and make informed engineering decisions—competencies increasingly demanded by modern industry (Renninger and Hidi 2015).

Fundamentals of Optimisation

An optimisation problem aims to find the design vector $\mathbf{x}$ that minimises or maximises one or more objective functions while satisfying equality and inequality constraints (Hillier 2005).

$$\begin{aligned} &\min_{\mathbf{x}} f(\mathbf{x}) \\ \text{s.t.}\quad &g_i(\mathbf{x}) \le 0 \\ &h_j(\mathbf{x}) = 0. \end{aligned}$$

The *objective function* represents a quantifiable goal, such as minimising cost or deflection. Constraints express limitations, such as maximum stress or geometry bounds. Together, they form the optimisation model.

Types of Optimisation Problems

In linear optimisation, both the objective function and constraints are linear in the variables. Such problems can be solved efficiently using the Simplex or interior-point algorithms. When the system behaviour or constraints are nonlinear, analytical solutions become difficult. Nonlinear programming (NLP) methods such as gradient descent or sequential quadratic programming (SQP) are commonly used. In many engineering contexts, multiple conflicting

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objectives exist. For instance, a lightweight beam may result in larger deflection. The outcome is a set of Pareto-optimal solutions representing trade-offs among objectives (Hillier 2005).

Solution Approaches

Analytical optimisation involves deriving closed-form relationships using calculus or Lagrange multipliers. While these methods are mathematically rigorous, they are limited to simplified geometries and loading conditions (Hillier 2005). When analytical formulations are infeasible, simulation-based optimisation offers an alternative by coupling numerical solvers (e.g., finite element analysis) with search algorithms. The main approaches include:

- **Response Surface Methodology (RSM)** — a statistical and numerical technique that builds surrogate models to approximate complex relationships.
- **Metaheuristics** — algorithmic approach such as genetic algorithm (GA), simulated annealing (SA), ant colony optimisation (ACO), particle swarm optimisation (PSO) that efficiently explore the search space in order to find optimal or near–optimal solutions.
- **Hybrid Adaptive Sampling** — combines DOE, surrogate modelling, and iterative refinement to reduce computation time.

Problem Statement

Students were tasked with designing a cantilever I-beam of fixed length L that must support a point load P at its free end. The beam's cross-section is a standard I-shape, defined by four geometric parameters. The goal was to find the best set of dimensions that simultaneously:

1. minimize the total mass (a direct proxy for material cost) and
2. minimize the maximum vertical deflection at the free end (a measure of stiffness and performance).

These two objectives are conflicting: a heavier, stiffer beam will deflect less but cost more, while a lighter beam will be cheaper but deflect more (Gere and Goodno 2018). Therefore, our optimisation problem is a classic problem in structural optimisation that is intuitive, has clear engineering constraints, and involves a direct trade-off between two key objectives:

1. cost (represented by mass) and
2. performance (represented by deflection).

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Design Variables

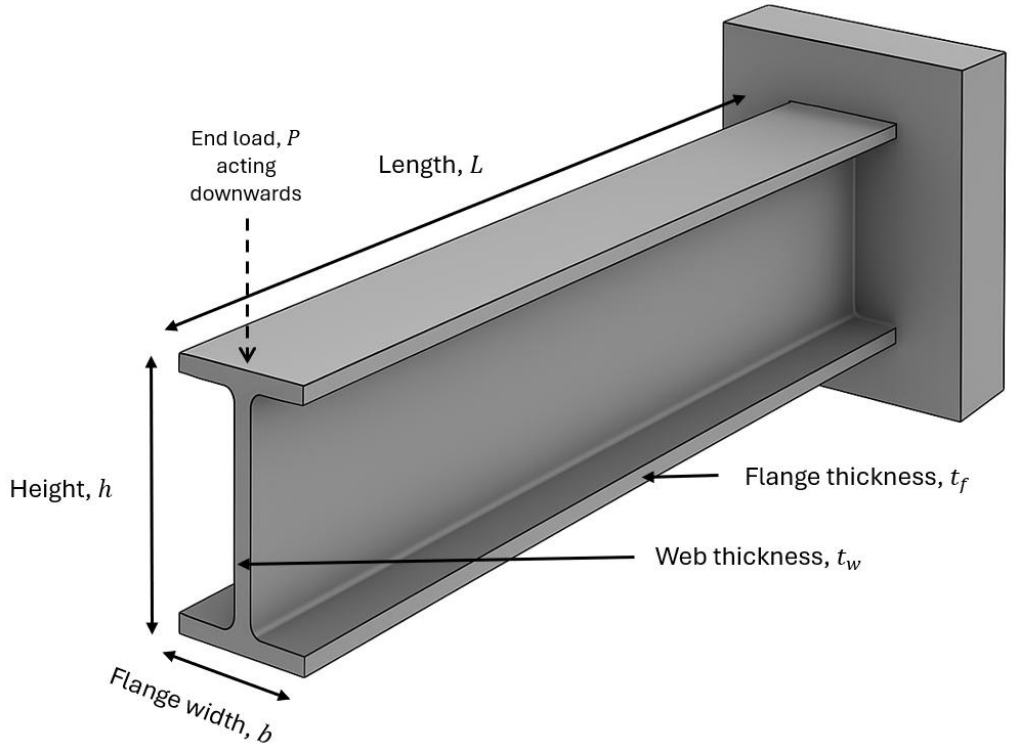
The cross-sectional dimensions of the I-beam are the design variables (Gere and Goodno 2018). Four key dimensions were used in standard I-beam profiles:

- h: height of the web (m),
- b: width of the flange (m),
- t_f: thickness of the flange (m),
- t_w: thickness of the web (m).

Hence, the design vector is

$$\mathbf{x} = [h,\ b,\ t_f,\ t_w].$$

Figure 1. *A three-dimensional model of a typical cantilever I-beam fixed at one end*



Objective functions

Our optimisation problem is a two-objective optimisation problem.

1. Minimize Mass, $f_1(\mathbf{x})$ The mass of the beam is

$$\text{Mass} = \rho\, L\, A_{\text{cross}},$$

where

- ρ is the material density (for steel, $\rho \approx 7850$ kg/m^3),
- L is the length of the beam (e.g., $L = 5$ m),
- A_{cross} is the cross-sectional area of the I-beam.

For the I-beam (Gere and Goodno 2018),

$$A_{\text{cross}} = 2bt_f + (h - 2t_f)t_w.$$

Thus, the first objective function is

$$f_1(\mathbf{x}) = \rho\, L\, A_{\text{cross}}(h, b, t_f, t_w).$$

2. Minimize Deflection, $f_2(\mathbf{x})$ For a cantilever beam with an end load P, the maximum deflection at the free end is (Gere and Goodno 2018)

$$\delta_{\max} = \frac{PL^3}{3EI},$$

where

- P is the point load at the free end (e.g., $P = 50$ kN),
- E is the Young's modulus of the material (for steel, $E \approx 200$ GPa),
- I is the second moment of area of the cross-section about the bending axis.

For an I-beam, the second moment of area about the centroidal x-axis is approximated (Gere and Goodno 2018) by

$$I = \frac{bh^3}{12} - \frac{(b - t_w)\,(h - 2t_f)^3}{12}.$$

The second objective function is then

$$f_2(\mathbf{x}) = \delta_{\max}(\mathbf{x}) = \frac{PL^3}{3EI(h, b, t_f, t_w)}.$$

Constraints

The beam must be feasible to manufacture and must not fail under loading. The following constraints were imposed.

1. Bending Stress Constraint: The maximum bending stress must not exceed the yield strength σ_y of the material (Gere and Goodno 2018). For a cantilever with end moment $M = PL$ and extreme fiber distance $y = h/2$, the bending stress is

$$\sigma_{\text{b}} = \frac{My}{I} = \frac{PL(h/2)}{I}.$$

The constraint is

$$\sigma_{\text{b}} \leq \sigma_y.$$

In inequality form,

$$g_1(\mathbf{x}) = \frac{PLh}{2I(h, b, t_f, t_w)} - \sigma_y \leq 0.$$

2. Geometric/Aspect Ratio Constraints: To ensure a practical and manufacturable I-section, slenderness and proportion constraints were applied:

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$$\text{Web slenderness:} \quad \frac{h}{t_w} \geq 50,$$

$$\text{Flange slenderness:} \frac{b}{t_f} \geq 10,$$

$$\text{Overall proportion:} \frac{h}{b} \leq 5.$$

3. Bounds on Design Variables: Manufacturing limitations and practical considerations impose lower and upper bounds on the design variables:

$$0.1\,\text{m} \leq h \leq 1.0\,\text{m},$$
$$0.05\,\text{m} \leq b \leq 0.5\,\text{m},$$
$$0.005\,\text{m} \leq t_f \leq 0.05\,\text{m},$$
$$0.005\,\text{m} \leq t_w \leq 0.05\,\text{m}.$$

ANSYS Workbench Experimental Setup

The optimisation problem, which is the optimal design of a Cantilever I-Beam, was set up in **ANSYS Workbench 2025 R1** using the DesignXplorer environment (ANSYS Inc. 2025). Students created a simulation model using ANSYS Workbench based on the objective functions and constraints, and parameter values given in Section 4 and 5. While developing the model, students also looked at the ANSYS_Workshop_Recording.mp4 file, which was created ahead of the delivered session. This problem is designed to give undergraduate students practical experience with a complete multi-objective optimisation workflow.

The workflow implemented in ANSYS DesignXplorer followed these three distinct stages:

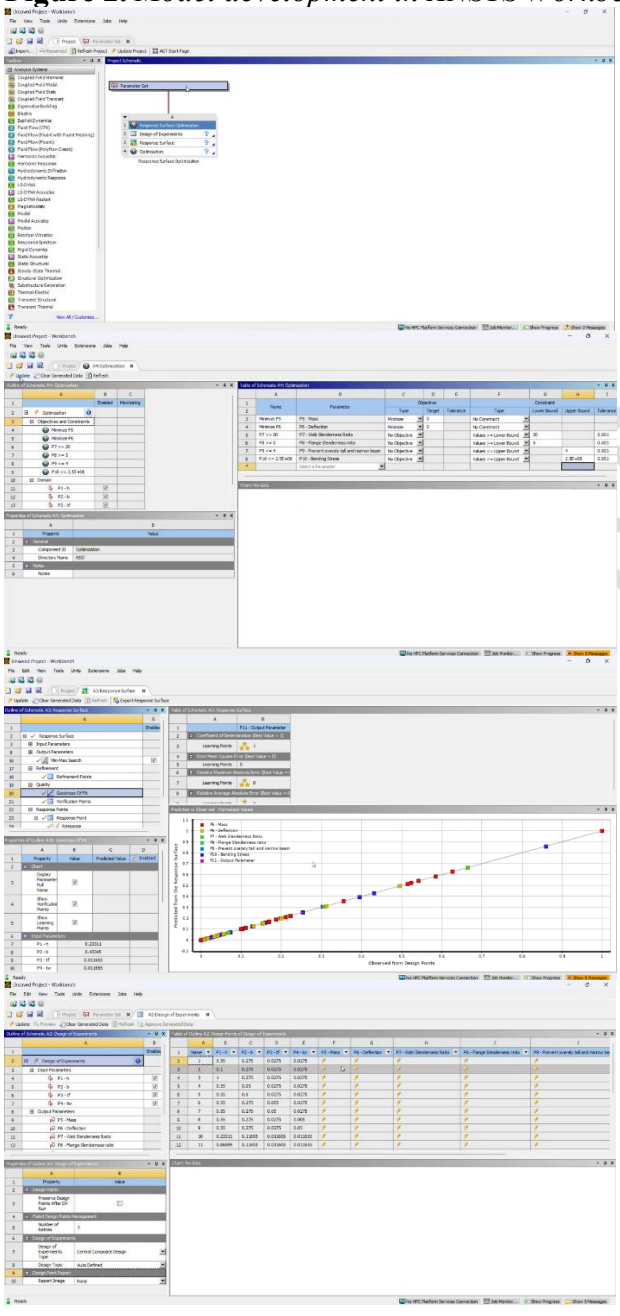
1. **Design of Experiments (DoE):** This stage involves selecting a set of design points (combinations of the design variables $x = (h, b, t_f, t_w)$ to efficiently explore the design space and gather data on the objectives (f_1 and f_2) and constraints.
2. **Response Surface:** After the DoE data is collected, a Response Surface Methodology (RSM) model was created. The response surface is an approximate mathematical function that relates the input design variables to the output objectives and constraints, allowing for faster evaluation than running the full finite element analysis for every design point.
3. **Optimisation:** Finally, the response surface model was used within the optimisation stage to find the best set of design variables (x) that meet the goals of simultaneously minimizing the total mass (f_1) and minimizing the maximum vertical deflection (f_2), while satisfying all defined constraints. Students used the Multi-Objective Genetic Algorithm (MOGA) in ANSYS Workbench to find the optimal point (optimal mass and deflection).

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Post-Processing and Visualisation

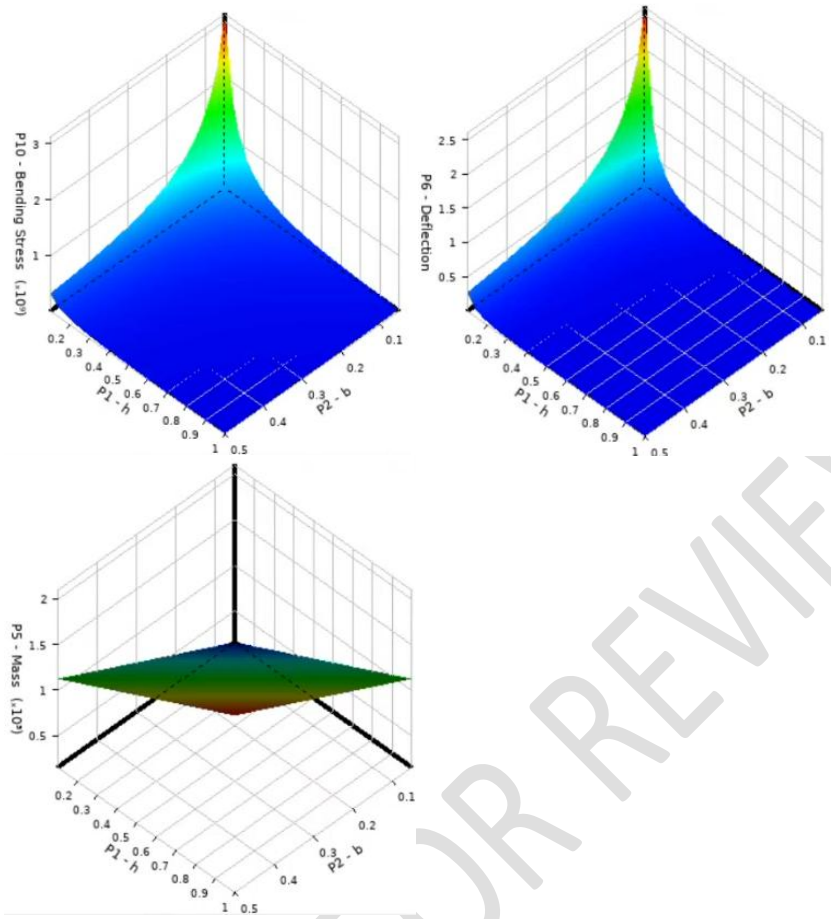
Once the model was developed, the main window, the design of experiment, response surface and optimisation window should look as shown in Figure 2, 3, 4, and 5.

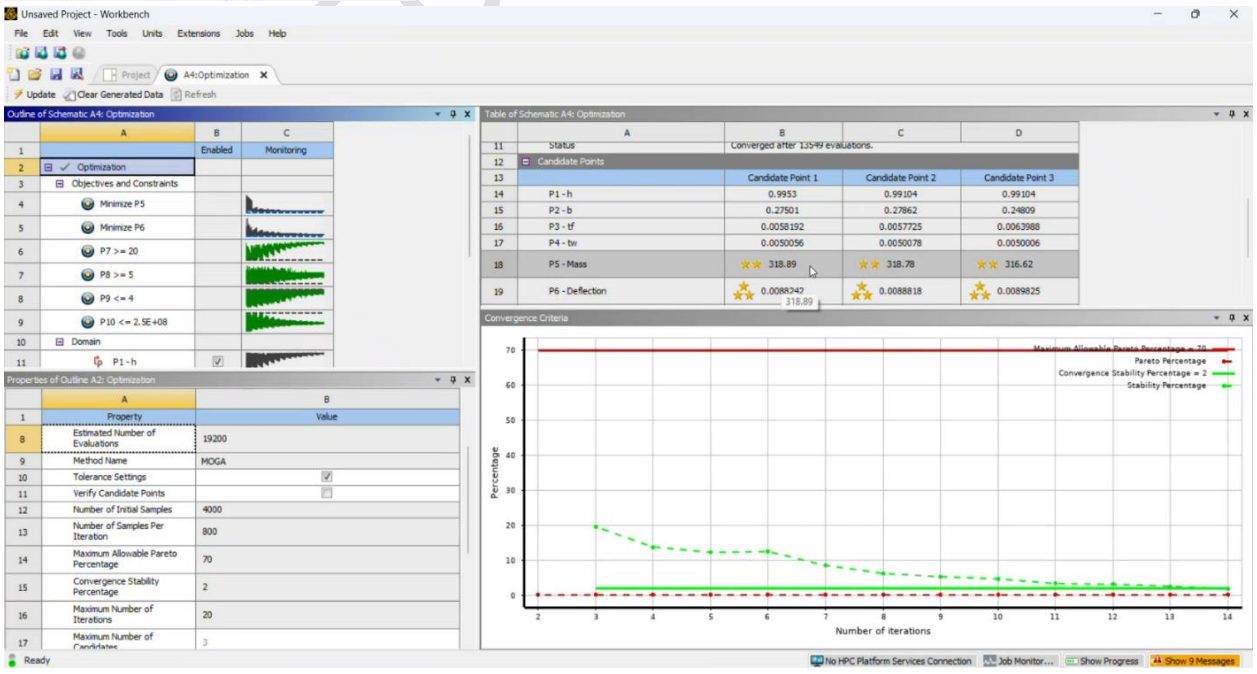
Figure 2. *Model development in ANSYS Workbench*



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Figure 3. *ANSYS model results for cantilever I-Beam*





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Students obtained the final optimal points table as given in "Table of Schematic A4: Optimisation" (as shown in Figure 4(d)) from where they chose the best optimal point for the cantilever I-beam. This problem gives undergraduate students hands-on experience with the complete multi-objective optimisation workflow, from problem formulation and modeling through to computational solution and engineering interpretation.

The resulting Pareto front (Figure 4(d)) illustrated the trade-off between lightweight and stiffness. The "knee point" on the curve represents the most balanced design.

Pedagogical Reflection

In line with the approach by Reith *et al.* (Reith et al. 2024), integrating simulation-based optimisation into the curriculum enhances comprehension of mathematical modelling and numerical analysis. Students are encouraged to interactively modify parameters, interpret Pareto trade-offs, and develop intuition for engineering decision-making.

The integration of ANSYS Workbench and response surface methodology (RSM) into the teaching of multi-objective optimisation proved to be highly effective in engaging undergraduate students and enhancing their conceptual understanding of engineering design trade-offs. A key pedagogical outcome observed during the activity was students' strong enthusiasm for interacting with professional-grade simulation software. Many students reported that they enjoyed "playing with" ANSYS Workbench—modifying geometric parameters, running simulations, and immediately visualising the impact of their design choices on mass, deflection, and stress responses. This sense of exploration fostered intrinsic motivation and sustained engagement throughout the session.

Importantly, the availability of a pre-developed ANSYS Workbench model (Cantilever_I_Beam), downloadable from Blackboard (VLE platform), significantly lowered the barrier of learning. Students were able to focus on design reasoning and interpretation rather than becoming overwhelmed by software setup or advanced mathematical derivations. Even students with limited prior exposure to optimisation theory or beam-bending mathematics were able to meaningfully participate. By adjusting parameters such as web height, flange width, and thicknesses, they could intuitively observe trends—such as the strong influence of beam height on stiffness—without first mastering the full analytical background. This aligns with constructivist learning principles, where understanding emerges through interaction and experimentation rather than passive derivation alone.

Despite this limited theoretical background, students consistently reported that the results "made sense" to them. The response surface plots, contour maps, and Pareto fronts provided clear visual representations of trade-offs between mass and deflection. For example, students intuitively recognised why increasing the beam height significantly reduced deflection while increasing mass, and why no single design could simultaneously minimise both objectives.

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The ability to visualise these relationships transformed optimisation from an abstract mathematical concept into a tangible engineering decision-making process.

Another key strength of the activity was the way ANSYS DesignXplorer presented the entire workflow—parameterisation, DoE sampling, surrogate modelling, and multi-objective optimisation—as a coherent and transparent process. Students could see how individual simulations contributed to response surfaces, and how these surfaces were then used by the genetic algorithm to search for optimal designs. This end-to-end visibility helped students develop a "big picture" understanding of optimisation, which is often difficult to achieve through purely analytical or code-based approaches.

Overall, the exercise demonstrated that professional simulation tools can be powerful pedagogical enablers. By allowing students to engage meaningfully with optimisation concepts before mastering the underlying mathematics, the activity built confidence, intuition, and motivation. It also mirrored real-world engineering practice, where engineers frequently rely on simulation-driven workflows to guide design decisions. As a result, students not only learned what optimisation is, but also why it matters and how it is applied in modern engineering contexts.

Beyond the immediate classroom observations, the pedagogical value of the activity can also be interpreted through established educational theories. One particularly relevant framework is Kolb's experiential learning theory (Kolb 2014), which emphasises learning through a cyclical process consisting of four stages: concrete experience, reflective observation, abstract conceptualisation, and active experimentation. The optimisation workshop naturally followed this learning cycle. Students first gained concrete experience by interacting directly with the ANSYS Workbench model and adjusting beam parameters. They then engaged in reflective observation by analysing simulation outputs such as response surfaces, contour plots, and Pareto fronts. These observations helped them form abstract conceptualisations about the relationship between structural geometry, stiffness, and material usage. Finally, students engaged in active experimentation by iteratively modifying design variables and evaluating alternative solutions. This experiential cycle helped reinforce theoretical optimisation concepts while promoting deeper conceptual understanding through direct computational exploration.

The learning activity can also be interpreted using the principle of constructive alignment, a widely recognised framework in higher education pedagogy proposed by Biggs and Tang (Tang and Biggs 2007). Constructive alignment emphasises the importance of aligning intended learning outcomes, teaching activities, and assessment tasks so that each component of the learning process supports the others. In the present study, the intended learning outcomes included understanding optimisation formulation, interpreting engineering trade-offs, and applying computational tools to analyse structural behaviour. The ANSYS-based optimisation workshop served as the primary teaching activity enabling students to explore these concepts in practice. Importantly, related optimisation problems and conceptual questions were incorporated into

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subsequent coursework and examinations, ensuring that assessment tasks reinforced the same learning objectives. This alignment between teaching activities and assessment helped encourage deeper engagement with the material and supported the development of analytical reasoning skills.

In addition to these theoretical pedagogical perspectives, the workshop produced observable improvements in student engagement and academic performance. Following the introduction of the optimisation workshop, teaching staff observed a noticeable increase in class attendance in subsequent lectures and tutorial sessions related to optimisation and structural analysis. Furthermore, improvements were observed in student examination performance compared with previous cohorts who had not participated in the simulation-based workshop.

Taken together, these outcomes indicate that integrating simulation-based optimisation exercises within engineering curricula can significantly strengthen both student engagement and conceptual understanding. By combining theoretical instruction with hands-on computational experimentation, the activity helped students connect mathematical optimisation principles with realistic engineering design workflows. Such integration supports the broader goals of contemporary engineering education, which emphasise the development of analytical reasoning, problem-solving capability, and familiarity with professional engineering tools.

Conclusion

This paper presented a teaching and learning approach for introducing undergraduate engineering students to multi-objective optimisation through the practical example of the optimal design of a cantilever I-beam. Rather than focusing solely on theoretical derivations, the activity combined analytical concepts from structural mechanics with simulation-based optimisation implemented in ANSYS Workbench. This approach enabled students to explore optimisation principles within a realistic engineering design environment and provided a concrete illustration of how objective functions, constraints, and design variables interact in real-world engineering problems.

A key contribution of this work lies in demonstrating how professional computer-aided engineering tools can be effectively integrated into the teaching of optimisation and mathematical modelling. Through the use of Design of Experiments, response surface methodology, and multi-objective optimisation within ANSYS DesignXplorer, students were able to visualise the relationships between design variables and structural performance measures such as mass and deflection. The resulting Pareto front provided a clear and intuitive representation of engineering trade-offs, helping students understand that optimisation often involves selecting a balanced design rather than identifying a single universally optimal solution.

From a pedagogical perspective, the workshop-based learning activity allowed students to actively engage with optimisation concepts through

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experimentation and visualisation. The interactive nature of the ANSYS model enabled students to modify parameters, observe simulation outcomes, and interpret optimisation results in real time. This experiential approach helped transform optimisation from an abstract mathematical topic into a practical engineering decision-making process. The activity also exposed students to industry-standard software workflows, thereby improving their familiarity with tools commonly used in professional engineering practice.

The educational outcomes of the activity were encouraging. Students demonstrated improved engagement with optimisation concepts, and the use of simulation-based exploration appeared to enhance conceptual understanding of structural design trade-offs. In addition, increased attendance in subsequent teaching sessions and improved performance in related examination questions suggest that the integration of computational experimentation can positively influence student motivation and learning outcomes.

Overall, the cantilever I-beam optimisation exercise provides a practical and scalable framework for teaching optimisation in engineering programmes. By combining theoretical modelling with hands-on simulation, the approach helps bridge the gap between mathematical theory and engineering practice. Future teaching developments may extend this framework to more complex design problems, incorporate additional optimisation algorithms, or integrate interdisciplinary applications involving fluid dynamics, thermal systems, or energy optimisation.

References

ANSYS Inc. 2025. *ANSYS CFX Reference Guide*. ANSYS Inc.

De Weer, Tom, Nicolas Lammens, and Karl Meerbergen. 2023. “A Multi-Objective Framework for Pareto Frontier Exploration of Lattice Structures.” *Structural and Multidisciplinary Optimization* 66 (5): 108.

Donnelly, R., and M. Fitzmaurice. 2005. *Collaborative Project-Based Learning in Higher Education*. Technological University Dublin Reports.

Forehand, Mary. 2010. “Bloom’s Taxonomy.” *Emerging Perspectives on Learning, Teaching, and Technology* 41 (4): 47–56.

Friesel, A., E. Tovar, and J. Hrad. 2022. “Preparing and Developing Skills for Better Employability for STEM and Engineering Graduates.” *Proc. EAEEIE Conf.*

Gere, James M., and Barry J. Goodno. 2018. *Mechanics of Materials*. 9th ed. Cengage Learning.

Hillier, Frederick S. 2005. *Introduction to Operations Research*. McGrawHill.

Kadivar, MR, MA Moghimi, P Sapin, and CN Markides. 2019. “Annulus Eccentricity Optimisation of a Phase-Change Material (PCM) Horizontal Double-Pipe Thermal Energy Store.” *Journal of Energy Storage* 26: 101030.

Kolb, David A. 2014. *Experiential Learning: Experience as the Source of Learning and Development*. FT Press.

Lee, Huei-Huang. 2019. *Finite Element Simulations with ANSYS Workbench 2019*. SDC publications.

Martins, Joaquim RRA, and Andrew Ning. 2021. *Engineering Design Optimization*. Cambridge University Press.

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Moghimi, MA, and G Ahmadi. 2018. “Wind Barriers Optimization for Minimizing Collector Mirror Soiling in a Parabolic Trough Collector Plant.” *Applied Energy* 225: 413–23.

Moghimi, MA, KJ Craig, and JP Meyer. 2017. “Simulation-Based Optimisation of a Linear Fresnel Collector Mirror Field and Receiver for Optical, Thermal and Economic Performance.” *Solar Energy* 153: 655–78.

Montgomery, D. C. 2023. *Design and Analysis of Experiments*. 10th ed. Wiley.

Nemati, H, MA Moghimi, and JP Meyer. 2021. “Shape Optimisation of Wavy Mini-Channel Heat Sink.” *International Communications in Heat and Mass Transfer* 122: 105172.

Nemati, H, MA Moghimi, P Sapin, and CN Markides. 2020. “Shape Optimisation of Air-Cooled Finned-Tube Heat Exchangers.” *International Journal of Thermal Sciences* 150: 106233.

Nemati, Hossain, Mohammad Moghimi Ardekani, Ali Cemal Benim, and Josua Meyer. 2022. “Optimization of Horizontal Annular Finned Tube Under Natural Convection Heat Transfer.” *Heat Transfer Engineering* 43 (17): 1451–63.

Neumann, J. W. 2013. “Developing a New Framework for Conceptualizing Student-Centered Learning.” *The Educational Forum* 77 (2): 161–75.

Papalambros, Panos Y. 2002. “The Optimization Paradigm in Engineering Design: Promises and Challenges.” *Computer-Aided Design* 34 (12): 939–51.

Reith, D., P. Spelten, F. Rossbach, V. Lueddemann, F. Dieball, and G. Steinebach. 2024. “Bringing Mathematical Modeling and Engineering Students Closer Together by Seamlessly Linking Theories, Methods, and Applications.” *Proc. IEEE Global Engineering Education Conf. (EDUCON)*.

Renninger, K. A., and S. Hidi. 2015. *The Power of Interest for Motivation and Engagement*. Routledge.

Tang, Catherine, and John Biggs. 2007. *Teaching for Quality Learning at University: What the Student Does*. Society for Research into Higher Education & Open University Press.

Zingoni, Alphose. 2025. *Engineering Materials, Structures, Systems and Methods for a More Sustainable Future*. CRC Press.

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