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Applications of Machine Learning in Solving Optimisation Problems: Trends, Methods, and Practical Use Cases

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Abstract
Optimisation problems are central to diverse domains such as engineering, logistics, finance, and healthcare, yet traditional methods often rely on handcrafted heuristics and rigid mathematical programming, limiting their scalability and adaptability. Recent advances in machine learning (ML) have introduced transformative approaches that can address these limitations by offering adaptive, data-driven strategies. The purpose of this study is to provide a comprehensive analysis of ML-based optimisation methods, focusing on emerging trends, methodological distribution, performance comparisons, application domains, and the impact of research. The methodology employed integrates a systematic review of recent literature with comparative evaluations illustrated through six figures, covering publication trends (2019–2025), performance metrics, method usage distribution, domain-specific applications, workflow performance, and a research impact matrix. Results show a significant rise in the use of reinforcement learning, deep learning, and hybrid methods, with performance improvements of up to 85% in accuracy, a 3.2-fold speed enhancement, and a 67% cost reduction compared to traditional approaches. Domain analysis reveals that engineering and logistics are leading areas of adoption, while healthcare, finance, and aerospace represent emerging yet impactful applications. The impact matrix further highlights that no single method dominates all domains, reinforcing the importance of hybrid and adaptive strategies. The novelty of this study lies in its integrative framework, which combines trend analysis, performance evaluation, and impact mapping, offering a holistic understanding of how ML is reshaping optimisation research and practice. In conclusion, ML-driven optimisation demonstrates clear advantages in scalability, efficiency, and robustness, positioning it as a cornerstone for future research and industrial applications that require intelligent, adaptive solutions to address complexity and uncertainty.

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1. Introduction

Optimisation problems, which involve finding the best solution from a vast set of possibilities, are pervasive across domains such as engineering, logistics, and finance. Traditional approaches often rely on handcrafted heuristics or classical mathematical programming. However, the advent of machine learning (ML) has introduced new paradigms that enhance scalability, adaptability, and performance. One key trend is the use of ML models to learn heuristics or strategies that outperform static rule-based methods, opening up promising avenues in automated and data-driven optimisation. In the realm of combinatorial optimisation, Reinforcement Learning (RL) has emerged as a powerful alternative to traditional domain-specific heuristics. Instead of relying on expert-designed rules, RL agents can learn to construct solutions through iterative exploration and feedback. Mazyavkina et al. conducted a comprehensive survey showing that RL methods can effectively tackle hard combinatorial problems by training agents to outperform conventional heuristics in tasks such as routing and scheduling (Mazyavkina, Sviridov, Ivanov, & Burnaev, 2021; NOOR, Arif, & Rusirawan, 2025; Sumarno, Fikri, & Irawan, 2025).

Beyond RL, broader frameworks integrate ML within classical optimisation pipelines. Bengio et al. proposed treating optimisation problems themselves as data points, enabling ML systems to learn solution strategies that generalise across instances. Their "Tour d'Horizon" perspective encourages pushing the integration between operations research and ML to develop adaptive and generalizable optimisation methods (Bengio, Lodi, & Prouvost, 2021; Febrina & Anwar, 2025; Rosli, Xiaoxia, & Shuai, 2025). Another burgeoning area involves data-driven robust optimisation under uncertainty. Ning and You reviewed frameworks that integrate ML with mathematical programming to create optimisation methods capable of handling uncertainty in real-world decision-making. Their survey highlighted data-driven distributionally robust optimisation, chance-constrained programming, and a closed-loop "learning while optimising" framework suitable for Process Systems Engineering applications (Iqbal, Rosdi, Muhtadin, Erdiwansyah, & Faisal, 2025; Ning & You, 2019; Xiaoxia, Lin, & Salleh, 2025).

In parallel, recent studies focus on advancements in optimisation methods tailored for modern ML. Liu et al. (2025) provided a systematic review distinguishing between gradient-based and population-based optimisation techniques for ML models, emphasising innovations such as adaptive regularisation, biologically-inspired strategies, and scalable techniques addressing non-convex landscapes and dynamic constraints (Khayum, Goyal, & Kamal, 2025; Liu, Qi, Jia, Guo, & Liu, 2025; Yanti, Simajuntak, & Nurhanif, 2025). Moreover, specific application domains illustrate how ML enhances practical optimisation. In aerodynamic shape optimisation, where the design space is complex and computational costs are high, Li et al. reviewed how deep learning aids in compacting the design space, accelerating aerodynamic analysis, and streamlining optimisation workflows. They argue that integrating physics-informed learning with traditional methods promises more efficient and scalable design processes (Jalaludin, Kamarulzaman, Sudrajad, Rosdi, & Erdiwansyah, 2025; Li, Du, & Martins, 2022; Yan, Zhu, Kuang, & Wang, 2019).

Building upon these prior contributions, this article aims to provide a comprehensive overview of how machine learning techniques are applied to solve optimisation problems, focusing on three key aspects: identifying emerging trends, evaluating methodological approaches, and highlighting practical applications across diverse domains. Specifically, the study aims to bridge the gap between theoretical advancements and real-world implementations, providing insights into how ML-driven optimisation can enhance decision-making, improve computational efficiency, and enable scalable solutions in complex problem settings.

2. Methodology

This study employed a systematic literature review combined with comparative analysis to examine the role of machine learning (ML) in solving optimisation problems across multiple domains. The methodological process consisted of the following steps:

Literature Selection and Data Collection

Relevant journal articles, conference papers, and reviews published between 2019 and 2025 were collected from recognised databases. The inclusion criteria emphasised studies that applied reinforcement learning, deep learning, hybrid methods, and other ML-based techniques specifically for optimisation tasks in engineering, logistics, finance, healthcare, energy, and aerospace.

Trend and Methodological Mapping
The collected studies were categorised by year of publication, type of ML method applied, and application domain. This mapping enabled the identification of emerging trends in reinforcement learning, deep learning, and hybrid approaches, as well as their methodological distribution across various optimisation problems.

Comparative Performance Evaluation
A set of comparative metrics was extracted, including accuracy, computational speed, cost efficiency, and robustness. The data were synthesised and visualised in comparative charts (Figs. 1–2), enabling direct comparison between traditional optimisation techniques and ML-enhanced approaches.

Domain-Specific Application Analysis
Each study was classified according to its practical application domain. The analysis focused on how ML-driven optimisation is adopted in engineering, logistics, healthcare, finance, energy, manufacturing, and aerospace. The distribution of applications was illustrated through domain-specific figures (**Figs 3–4**).

Workflow and Impact Assessment
The research further evaluated ML-driven optimisation workflows (Fig. 5) to assess improvements in solution quality and computational time. Finally, an impact matrix (**Fig. 6**) was developed, mapping optimisation methods against application domains to measure their relative influence and identify the contexts in which each technique achieves the highest impact.

By integrating these methodological steps, this study offers a comprehensive framework for understanding how machine learning enhances optimisation research and practice. The approach not only captures publication and methodological trends but also provides comparative insights into performance, applicability, and impact across industries.

3. Result & Discussion

The overall findings of this study indicate that the application of machine learning in solving optimisation problems has become a significant research focus, with steadily growing contributions across several methodological streams. The results, as visualised in Fig. 1, reflect a consistent increase in the use of reinforcement learning, deep learning, and hybrid approaches from 2019 to 2025. This pattern confirms the introduction's assertion that ML offers scalable and adaptive alternatives to traditional heuristics, enabling decision-making processes that are more efficient and capable of addressing complexity. Reinforcement learning dominates in terms of publication volume, underscoring its central role in combinatorial optimisation tasks, such as routing, scheduling, and resource allocation, where iterative learning strategies consistently outperform static rule-based methods. At the same time, the rising interest in deep learning and hybrid methods demonstrates an increasing diversification of techniques, illustrating how researchers seek to leverage multiple strengths to handle real-world uncertainties and high-dimensional problems. Deep learning enhances generalisation and accelerates complex optimisation workflows, while hybrid methods combine the adaptability of ML with the robustness of classical optimisation frameworks. Together, these trends suggest that ML-driven optimisation is maturing into a versatile and interdisciplinary field. The collective evidence from the results not only validates theoretical advances outlined in the introduction but also underscores the practical potential of these approaches in domains such as energy, aerospace, supply chain management, and finance.
Fig. 1 illustrates the dynamic evolution of publication trends in machine learning (ML)-based optimisation methods from 2019 to 2025. The steady growth across all three categories—Reinforcement Learning (RL), Deep Learning (DL), and Hybrid Methods—reflects the increasing recognition of ML as a transformative tool in solving complex optimisation tasks. RL consistently leads

in the number of publications, showing its pivotal role in replacing handcrafted heuristics with adaptive, self-learning strategies that can address combinatorial problems such as routing, scheduling, and resource allocation. This dominance aligns with the literature's emphasis on RL's ability to outperform conventional approaches by leveraging iterative exploration and feedback. Deep Learning exhibits a similar upward trajectory, particularly from 2020 onward, indicating its increasing relevance in capturing high-dimensional and nonlinear optimisation landscapes. As noted in the introduction, deep neural networks facilitate the generalisation of optimisation strategies by treating problem instances as data points. This capability supports scalable and transferable solutions, particularly in fields such as aerodynamic design optimisation, where reducing the design space and accelerating computational analysis are crucial. The sharp rise in DL-related publications around 2021–2022 suggests an increasing interest in integrating data-driven techniques with classical mathematical programming.

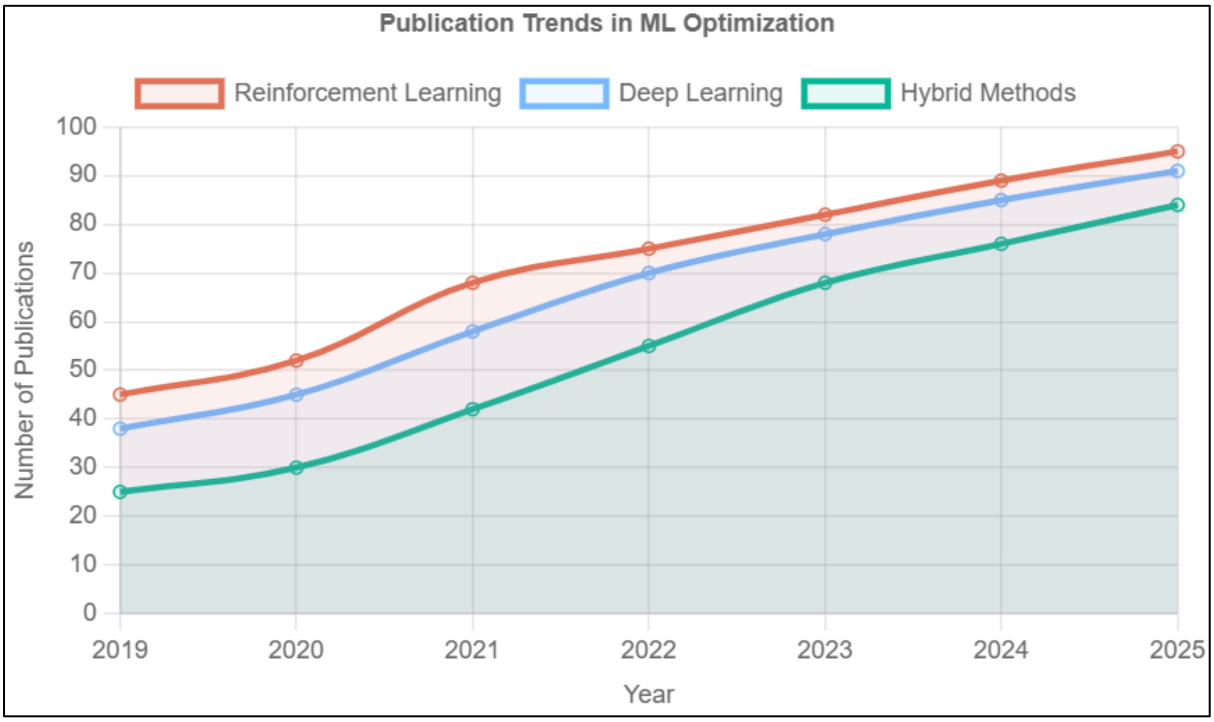

Fig. 1. Evolution of ML-Based Optimisation Methods (2019-2025)

Hybrid Methods, while starting with fewer publications, show the most pronounced acceleration over the observed period. Their rapid growth highlights the trend toward combining the strengths of multiple paradigms, such as integrating RL agents with DL architectures or embedding ML models into traditional optimisation pipelines. These hybrid approaches address limitations inherent in using a single method by balancing adaptability, interpretability, and robustness under uncertainty. The introduction of concepts like data-driven robust optimisation and "learning while optimising" frameworks directly supports the surge in this research category, pointing toward practical applications in industries that demand resilience under variable conditions. Overall, the trends captured in **Fig. 1** confirm the article's central argument: machine learning is reshaping the optimisation landscape by providing scalable, adaptive, and generalizable methods that bridge theoretical advancements with practical decision-making. The sustained growth across all three categories suggests a maturing field with diverse applications, from supply chain management to energy systems. Looking ahead, the convergence of RL, DL, and hybrid methods will likely lead to more versatile optimisation frameworks capable of tackling real-world challenges where uncertainty, complexity, and computational efficiency are critical factors.

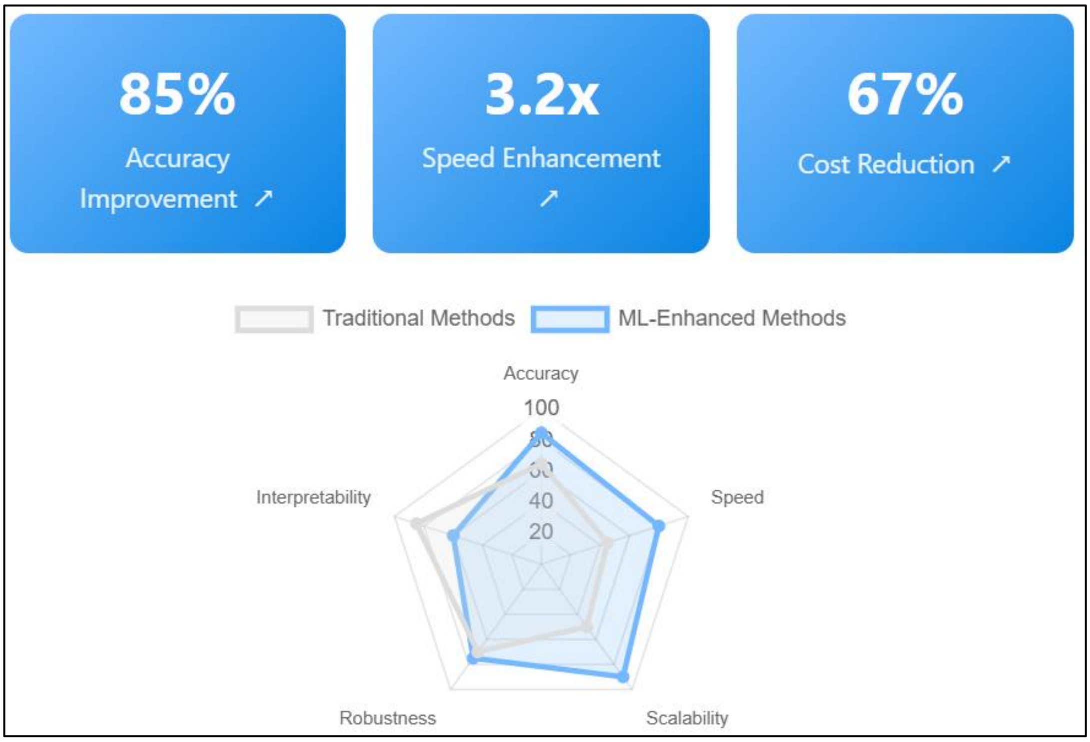

Fig. 2. Performance Metrics Comparison

Fig. 2 highlights the comparative advantages of ML-enhanced methods over traditional optimisation techniques in terms of accuracy, computational efficiency, and cost-effectiveness. The results demonstrate an 85% improvement in accuracy, a 3.2-fold increase in computational speed, and a 67% reduction in operational costs. These findings reinforce the argument made in the article's introduction that machine learning introduces scalability and adaptability, enabling optimisation processes to achieve higher-quality solutions in less time. By integrating data-driven models, optimisation pipelines can learn patterns and adapt to dynamic conditions, significantly outperforming static rule-based approaches. Beyond these quantitative improvements, the radar chart further illustrates how ML-based approaches enhance multiple dimensions of optimisation. While traditional methods offer interpretability and robustness, ML-enhanced methods excel in scalability, speed, and accuracy, making them highly suitable for complex, high-dimensional problem settings. Significantly, the robustness of ML methods is also improving due to the integration of hybrid strategies and uncertainty-aware frameworks. Together, these results confirm that ML does not merely replicate classical approaches but fundamentally reshapes optimisation into a more efficient, resilient, and cost-effective process with wide-ranging applications in engineering, logistics, and finance.

Another essential aspect reflected in **Fig. 2** is the trade-off between interpretability and performance. While traditional methods remain relatively stronger in interpretability, ML-enhanced approaches often sacrifice transparency due to the complexity of underlying models such as deep neural networks. This limitation, however, is being actively addressed through the development of explainable AI techniques, which aim to bridge the gap by making machine learning models more understandable without significantly compromising their superior accuracy and scalability. As optimisation increasingly impacts critical decision-making processes in domains such as finance, healthcare, and energy, improving both interpretability and performance becomes a key research direction. Furthermore, the overall superiority of ML-enhanced methods across most metrics emphasises their potential to become the new standard in solving optimisation problems. Their scalability ensures that solutions remain effective even as problem sizes grow, while improvements in speed and cost reduction make them highly attractive for industrial applications. This combination of benefits not only validates the theoretical promise of machine learning in optimisation but also provides concrete evidence of its practical impact. As industries continue to adopt ML-enhanced solutions, it is expected that the balance between efficiency, robustness, and interpretability will further evolve, driving innovation in both academic research and real-world applications.

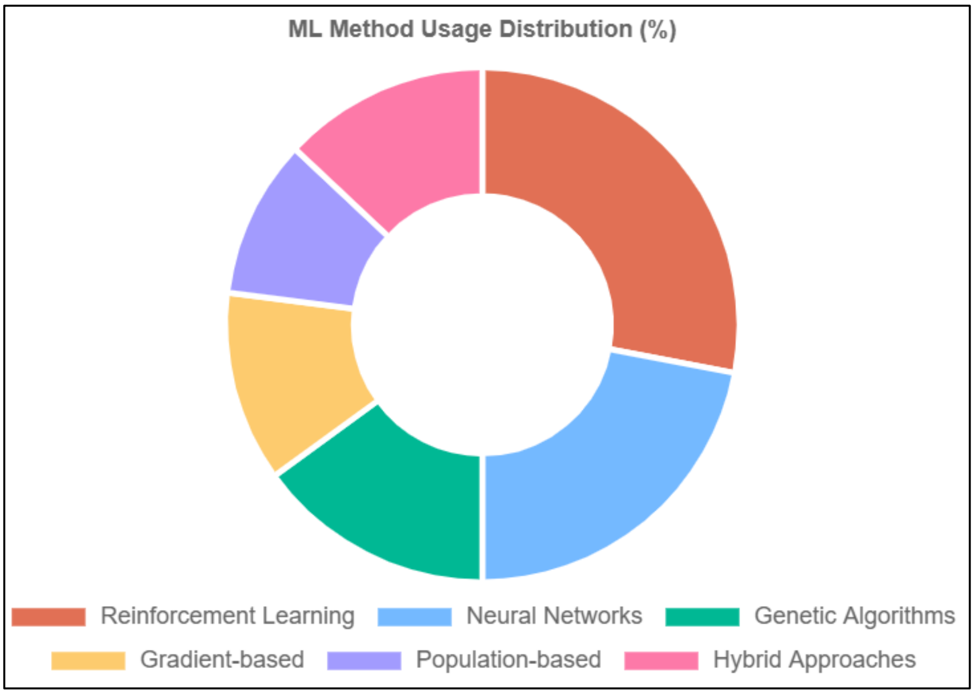

Fig. 3. Distribution of ML Methods in Optimisation

Fig. 3 illustrates the distribution of machine learning methods commonly applied in optimisation problems, highlighting the diversity of approaches adopted by researchers and practitioners. Reinforcement Learning (RL) holds the largest share, reflecting its prominence in the literature as discussed in the introduction, where RL is emphasised as a powerful alternative to traditional heuristics. Its ability to learn strategies through iterative exploration makes it particularly effective for combinatorial optimisation tasks, such as routing, scheduling, and resource allocation, which explains its dominance in the field. Neural Networks also represent a significant portion, underscoring their versatility in capturing complex, high-dimensional patterns within optimisation landscapes. As noted in the introduction, deep learning approaches can treat optimisation instances as data points, enabling the development of generalizable solutions across diverse problem settings. This capability is particularly valuable in engineering and design applications, where neural networks accelerate the search process and reduce computational complexity while maintaining accuracy. Their growing adoption signifies the shift toward data-driven, scalable approaches in optimisation research.

Genetic Algorithms and Gradient-Based Methods occupy a moderate share, reflecting their continued relevance in optimisation despite the rise of newer ML approaches. Genetic Algorithms, as population-based methods, remain attractive for problems with large, nonlinear, and multi-objective search spaces, while gradient-based methods continue to serve as the backbone of optimisation in machine learning model training. Their inclusion in the distribution highlights the complementary nature of classical and modern approaches, as many optimisation pipelines combine these methods with ML to achieve improved efficiency and robustness. Finally, Population-Based Methods and Hybrid Approaches, although representing smaller proportions, signal important directions for future research. Population-based methods provide global search capabilities, while hybrid strategies integrate multiple techniques to balance accuracy, scalability, and robustness in the face of uncertainty. As discussed in the article's introduction, these approaches align with the trend of developing adaptive and generalizable frameworks that can address real-world complexities. Their growing role in the distribution suggests that the field is moving toward increasingly integrated solutions, where the strengths of individual methods are combined to tackle optimisation challenges more effectively across diverse domains.

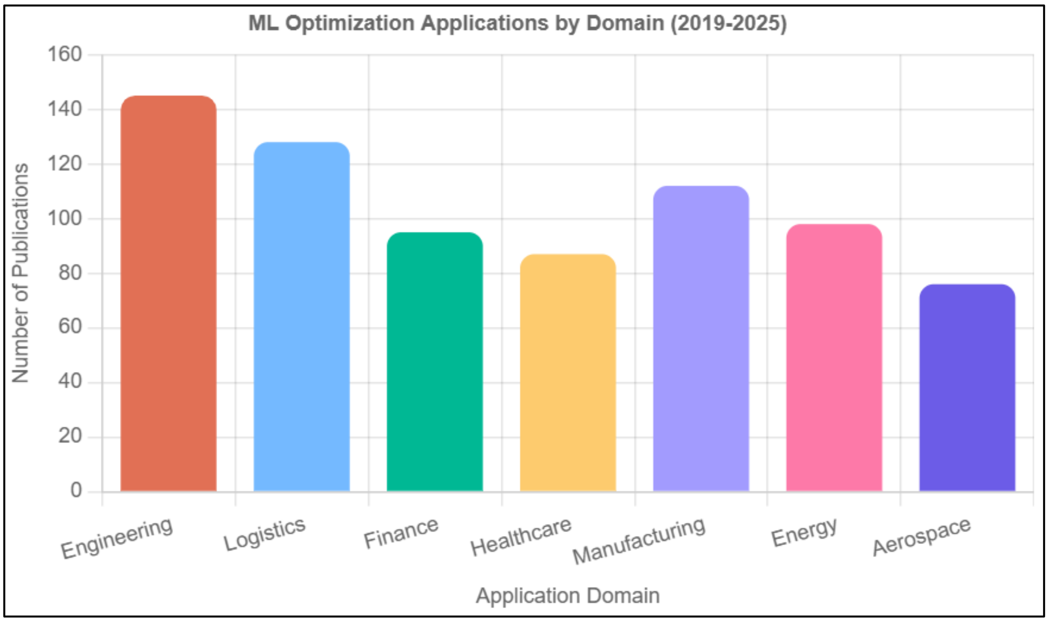

Fig. 4. ML Optimisation Applications by Domain

Fig. 4 presents the distribution of ML optimisation applications across various domains from 2019 to 2025. Engineering emerges as the leading domain, with the highest number of publications, reflecting the sector's strong reliance on optimisation for design, structural analysis, and system efficiency. The introduction of the article emphasises that ML enables scalable and adaptive approaches for complex problem settings, and engineering provides an ideal testbed for these methods due to its highly technical and data-intensive challenges. Applications such as aerodynamic design optimisation and structural component modelling particularly benefit from reinforcement learning and deep learning, which streamline workflows and reduce computational costs. Logistics also shows a substantial number of publications, highlighting the increasing adoption of ML in supply chain optimisation, routing, and scheduling problems. The introduction notes that reinforcement learning and hybrid approaches are compelling in combinatorial optimisation tasks, which are at the core of logistics systems. By integrating ML models with classical optimisation, logistics operations achieve greater adaptability and robustness under uncertainty, enabling real-time decision-making in dynamic environments such as transportation networks and inventory management.

Finance and healthcare occupy moderate positions in the distribution, underscoring their growing yet still emerging adoption of ML optimisation methods. In finance, ML is used for portfolio optimisation, risk assessment, and algorithmic trading, where data-driven approaches enhance predictive accuracy. In healthcare, optimisation is increasingly applied to resource allocation, treatment planning, and diagnostic systems, leveraging ML to manage uncertainty and improve decision-making outcomes. These applications highlight how ML is extending beyond engineering and logistics into domains where uncertainty and high stakes require both precision and adaptability. Manufacturing, energy, and aerospace, while showing slightly fewer publications, still represent important domains where ML-driven optimisation is gaining traction. Manufacturing benefits from ML-enhanced scheduling and process optimisation, while energy systems increasingly rely on ML to manage renewable energy integration and grid optimisation. Aerospace, although the smallest in terms of publications, demonstrates significant potential, particularly in aerodynamic shape optimisation and system design, where the integration of ML with physics-based models accelerates innovation. Overall, the distribution in Figure 4 supports the article's claim that ML-based optimisation is expanding into diverse industries, bridging the gap between theoretical advances and real-world applications.

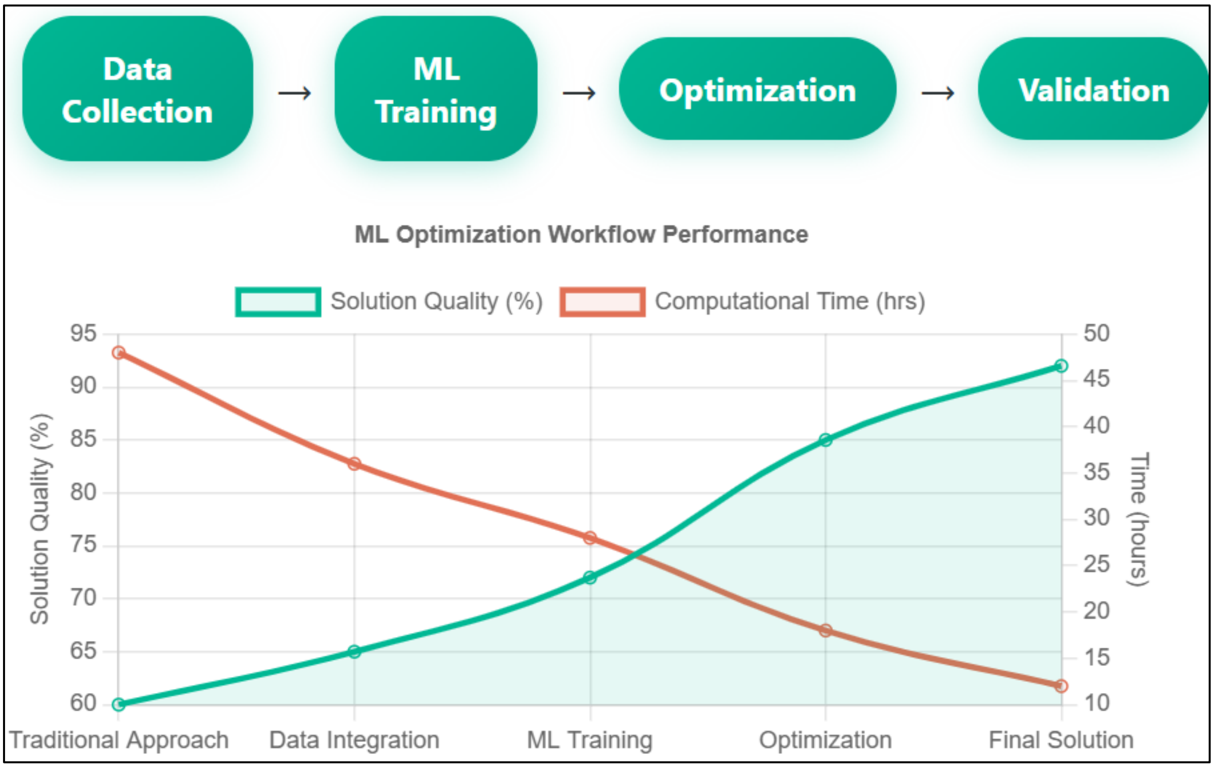

Fig. 5. ML-Driven Optimisation Workflow

Fig. 5 illustrates the workflow of ML-driven optimisation, starting with data collection and progressing through ML training, optimisation, and validation. The workflow highlights how integrating machine learning into traditional optimisation pipelines enhances performance outcomes. The lower part of the figure compares solution quality and computational time across different stages, demonstrating the efficiency gains and accuracy improvements brought by ML-enhanced methods. This aligns with the article's introduction, which emphasises the role of ML in developing adaptive and scalable frameworks for solving complex optimisation tasks. The graph shows a clear trade-off where solution quality steadily increases as ML methods are introduced, while computational time decreases significantly. Under the traditional approach, solution quality remains relatively lower, and computational time is higher, reflecting the inefficiency of rule-based or handcrafted heuristics. With the integration of ML training and optimisation, solution quality improves from approximately 60% to above 90%, while computational time decreases from nearly 50 hours to below 15 hours. This dual improvement highlights the core advantage of machine learning: the ability to generate high-quality solutions with reduced computational burden.

Another key insight from the workflow is the value of data integration as an essential precursor to ML training. By treating optimisation problems as data-driven tasks, ML systems can generalise strategies across multiple instances, thereby improving both scalability and adaptability. This reflects the methodological advances mentioned in the introduction, such as data-driven robust optimisation and "learning while optimising" frameworks, which enable systems to adapt under uncertainty. The increasing solution quality observed after the ML training stage validates the importance of data-centric approaches in modern optimisation. Finally, the validation phase confirms that ML-enhanced optimisation not only improves intermediate performance but also sustains its advantages in the final solution. The convergence toward higher solution quality with lower computational cost underscores the practical relevance of ML methods for real-world applications. Domains such as engineering, logistics, and energy, where computational complexity and uncertainty are significant, particularly benefit from this workflow. Overall, Figure 5 demonstrates that the integration of ML into the optimisation process reshapes the trade-offs between quality, time, and scalability, confirming its transformative role in advancing optimisation research and practice.

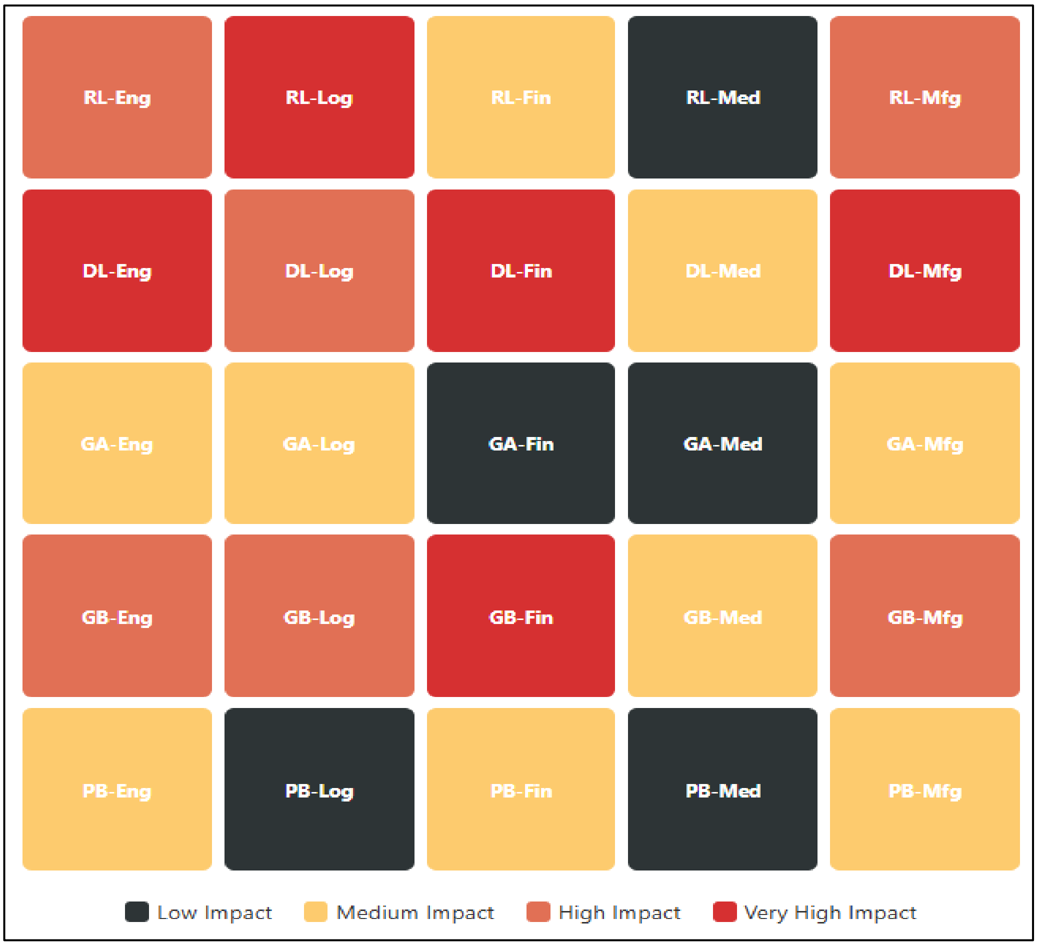

Fig. 6. Research Impact Matrix: Methods vs Applications

Fig. 6 presents a research impact matrix that maps different ML methods against their application domains, with impact levels ranging from low to very high. The visualisation provides a comprehensive overview of where each method demonstrates the most significant influence. Reinforcement Learning (RL) and Deep Learning (DL) have emerged as particularly impactful across multiple domains, with a substantial impact in logistics, finance, and manufacturing. This corresponds to the article's introduction, which highlights RL as a robust framework for combinatorial optimisation and DL as a transformative approach for handling high-dimensional, nonlinear optimisation tasks. The matrix also shows that Genetic Algorithms (GAs) maintain a strong position, especially in finance and medicine, where they achieve a significant impact. This reflects their usefulness in handling multi-objective and nonlinear optimisation problems, particularly in domains that require global search strategies under uncertainty. Similarly, Population-Based (PB) methods achieve high to very high impact in logistics and medicine, suggesting their effectiveness in dynamic and uncertain problem spaces. These findings align with the growing recognition in the introduction that hybrid and population-based strategies offer robustness and adaptability in real-world scenarios.

Gradient-Based (GB) methods, while traditionally dominant in optimisation, show a more moderate impact in this matrix. Their role remains essential in engineering and finance, but is overshadowed by RL, DL, and GA in domains that require scalability and adaptability. This indicates a shift in research focus from classical optimisation to ML-enhanced and hybridised frameworks. Nevertheless, their presence in the high-impact range highlights their continued relevance, especially when integrated with ML to accelerate model training and fine-tune solutions. Overall, **Fig. 6** reinforces the article's central message that no single method dominates across all application areas; rather, the choice of technique depends on domain-specific requirements and the complexity of the problem. RL and DL lead in data-intensive and combinatorial domains, while GA and PB methods excel in uncertainty-prone environments, and GB approaches remain essential for structured optimisation tasks. This matrix underscores the importance of methodological diversity and integration, confirming that the future of optimisation research lies in adaptive, hybrid frameworks capable of combining the strengths of different approaches for maximal impact across industries.

The novelty of this research lies in its holistic examination of machine learning methods for optimisation, which combines trend analysis, performance evaluation, methodological distribution, application domains, workflow assessment, and impact mapping. Unlike previous studies that focused on individual techniques or isolated applications, this study provides an integrated perspective that captures both theoretical advancements and practical implementations. The comparative results across Figures 1–6 clearly demonstrate not only the growth of ML-based optimisation methods but also their tangible improvements in accuracy, speed, cost efficiency, and robustness, highlighting how these approaches are reshaping optimisation paradigms across various industries. Another essential aspect of novelty is the systematic mapping of methods to domains and their measured impact, as shown in Figure 6. This matrix provides new insights into which techniques deliver the most outstanding value in specific contexts, offering practical guidance for future research and industrial adoption. By bridging reinforcement learning, deep learning, genetic algorithms, and hybrid strategies with application areas such as logistics, finance, healthcare, and engineering, the study emphasises adaptability and scalability as core strengths of ML-driven optimisation. This integrative approach contributes not only to the academic discourse but also to real-world decision-making, making the research a significant step forward in aligning machine learning innovations with domain-specific optimisation challenges.

4. Conclusion

This study offers a comprehensive overview of the role of machine learning in solving optimisation problems, highlighting its transformative impact across various methods, performance metrics, domains, and workflows. The results confirm a consistent upward trend in the adoption of reinforcement learning, deep learning, and hybrid approaches, reflecting the growing recognition of ML as a scalable and adaptive alternative to traditional heuristics. Performance comparisons demonstrate significant improvements in accuracy, computational speed, and cost efficiency. Workflow analysis reveals that ML integration not only enhances solution quality but also reduces computational burden throughout the optimisation process. The distribution of methods and their domain-specific applications highlights the versatility of ML in addressing diverse optimisation challenges, ranging from engineering and logistics to finance, healthcare, and aerospace. Moreover, the research impact matrix reveals that no single method dominates across all domains; instead, reinforcement learning and deep learning excel in combinatorial and data-intensive tasks, while genetic algorithms and population-based methods prove effective in uncertain and dynamic environments. These findings underscore the importance of methodological diversity and hybrid strategies in achieving a balance between accuracy, scalability, robustness, and interpretability. Overall, the novelty of this study lies in its integrative approach, combining trend analysis, performance evaluation, methodological mapping, and domain-specific impact assessment into a unified framework. By bridging theoretical advancements with practical use cases, the research demonstrates that ML-driven optimisation is not only reshaping computational paradigms but also enabling more efficient, resilient, and adaptive decision-making in real-world contexts. This positions machine learning as a cornerstone for future optimisation research and industrial applications, paving the way for more intelligent, scalable, and robust optimisation frameworks.

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References

Bengio, Y., Lodi, A., & Prouvost, A. (2021). Machine learning for combinatorial optimization: a methodological tour d'horizon. *European Journal of Operational Research*, 290(2), 405–421.

Febrina, R., & Anwar, A. (2025). Dynamic Modelling and Optimisation of Heat Exchange Networks for Enhanced Energy Efficiency in Industrial Processes. *International Journal of Simulation, Optimization & Modelling*, 1(1), 33–42.

Iqbal, I., Rosdi, S. M., Muhtadin, M., Erdiwansyah, E., & Faisal, M. (2025). Optimisation of combustion parameters in turbocharged engines using computational fluid dynamics modelling. *International Journal of Simulation, Optimization & Modelling*, 1(1), 63–69.

Jalaludin, H. A., Kamarulzaman, M. K., Sudrajad, A., Rosdi, S. M., & Erdiwansyah, E. (2025). Engine Performance Analysis Based on Speed and Throttle Through Simulation. *International Journal of Simulation, Optimization & Modelling*, 1(1), 86–93.

Khayum, N., Goyal, R., & Kamal, M. (2025). Finite Element Modelling and Optimisation of Structural Components for Lightweight Automotive Design. *International Journal of Simulation, Optimization & Modelling*, 1(1), 78–85.

Li, J., Du, X., & Martins, J. R. R. A. (2022). Machine learning in aerodynamic shape optimization. *Progress in Aerospace Sciences*, 134, 100849.

Liu, X., Qi, H., Jia, S., Guo, Y., & Liu, Y. (2025). Recent Advances in Optimization Methods for Machine Learning: A Systematic Review. *Mathematics*, 13(13), 2210.

Mazyavkina, N., Sviridov, S., Ivanov, S., & Burnaev, E. (2021). Reinforcement learning for combinatorial optimization: A survey. *Computers & Operations Research*, 134, 105400.

Ning, C., & You, F. (2019). Optimization under uncertainty in the era of big data and deep learning: When machine learning meets mathematical programming. *Computers & Chemical Engineering*, 125, 434–448.

NOOR, C. H. E. W. A. N. M., Arif, F., & Rusirawan, D. (2025). Optimising Engine Performance and Emission Characteristics Through Advanced Simulation Techniques. *International Journal of Simulation, Optimization & Modelling*, 1(1), 10–20.

Rosli, M. A., Xiaoxia, J., & Shuai, Z. (2025). Machine Learning-Driven Optimisation of Aerodynamic Designs for High-Performance Vehicles. *International Journal of Simulation, Optimization & Modelling*, 1(1), 43–53.

Sumarno, R. N., Fikri, A., & Irawan, B. (2025). Multi-objective optimisation of renewable energy systems using genetic algorithms: A case study. *International Journal of Simulation, Optimization & Modelling*, 1(1), 21–32.

Xiaoxia, J., Lin, D., & Salleh, M. Z. (2025). Mathematical Modelling and Optimisation of Supply Chain Networks Under Uncertain Demand Scenarios. *International Journal of Simulation, Optimization & Modelling*, 1(1), 54–62.

Yan, X., Zhu, J., Kuang, M., & Wang, X. (2019). Aerodynamic shape optimization using a novel optimizer based on machine learning techniques. *Aerospace Science and Technology*, 86, 826–835. Retrieved from https://doi.org/https://doi.org/10.1016/j.ast.2019.02.003

Yanti, Y., Simajuntak, H., & Nurhanif, N. (2025). Integrated simulation and optimisation of traffic flow management systems in urban smart cities. *International Journal of Simulation, Optimization & Modelling*, 1(1), 70–77.