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ARTIFICIAL INTELLIGENCE APPLICATION FOR SOLVING MIXED INTEGER LINEAR PROGRAMMING WITH LEARNING OPTIMIZATION TECHNIQUES IN AIR TRANSPORTATION AND MOBILITY: A NARRATIVE LITERATURE REVIEW

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ABSTRACT

Solving complex optimization problems in air transportation and mobility can be greatly improved by combining Mixed Integer Linear Programming (MILP) with modern computational techniques. Although MILP provides a solid framework for modeling these challenges, which often involve complex combinatorial structures and discrete decisions, traditional solution methods frequently struggle with the computational demands of real-world scenarios' scale and dynamic nature, largely due to their inherent NP-hard complexity. This narrative literature review highlights how integrating artificial intelligence methods enhances MILP, specifically focusing on Learning to Optimize (L2O) techniques. The L2O approach uses data-driven strategies, learning from historical operational data to improve how optimization algorithms function automatically. Instead of relying on heuristics, these methods can adaptively guide the search for solutions—such as predicting promising pathways or pruning unpromising ones—resulting in quality solutions with known optimality gap. Practical applications of these combined approaches are examined in key areas, such as flight scheduling, airport resource allocation, air traffic management, smart transportation systems, and route optimization. Analysis shows that integrating these methods with MILP can significantly improve operational efficiency, reduce computational time, and support more adaptive and reliable decision-making in complex transportation networks. By providing a comprehensive overview of the current state of the art, the research demonstrates the tangible potential of data-informed optimization to advance the transportation sector by overcoming the longstanding limitations of traditional approaches, ultimately fostering more resilient and efficient air transportation and mobility systems.

Keywords: Artificial Intelligence, Mixed Integer Linear Programming, Learning to Optimize, Air Transportation, Air Mobility.

GENERATIVE AI USAGE STATEMENT

The authors declare that the use of generative AI tools was restricted to technical support activities, without compromising the originality, analysis, and conclusions presented in the work. All information obtained through these resources was carefully evaluated and integrated into the study, ensuring methodological rigor and academic integrity. Scispace, Semantic Scholar, ChatGPT and NotebookLM were used for automated research, enhancing the search for references related to the study topics, and Jenni.ai was used to review the text.

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1 INTRODUCTION

Integrating artificial intelligence (AI) with mixed integer linear programming (MILP) techniques has become known as a transformative approach for tackling complex optimization problems across various domains, particularly in air transportation and mobility (Feng et al., 2020; Mirindi, 2024). MILP provides a robust framework for modeling combinatorial optimization problems through linear constraints and integer variables, offering extensibility for incorporating additional constraints expressed in a linear form (Blockeel et al., 2023). The recent progress in algorithms designed for solving MILP problems, paired with commercial and academic software packages, has broadened its applicability (Scavuzzo, Aardal, Lodi, et al., 2024). Nevertheless, conventional methods often struggle with the computational complexities of large-scale and dynamic real-world scenarios. With its capacity to learn from data, recognize patterns, and make predictions, AI presents complementary tools to improve MILP methodologies. This synergy unlocks new possibilities for optimizing intricate systems, enhancing decision-making processes, and improving operational efficiency. The intersection of machine learning and mathematical optimization presents an exciting avenue for improving the core components of branch-and-bound algorithms central to MILP solvers (Scavuzzo, Aardal, Lodi, et al., 2024).

The integration of machine learning with MILP has spurred substantial interest in both academia and industry, motivated by the potential to enhance the efficiency, scalability, and robustness of optimization systems. The fusion of these two fields offers opportunities to develop innovative solution methodologies that leverage the strengths of both machine learning and mathematical optimization (Scavuzzo, Aardal, Lodi, et al., 2024). This paper aims to explore the application of AI in solving MILP problems, with a particular emphasis on employing learning to optimize techniques. The objective is to offer a comprehensive overview of the current state-of-the-art research, highlight key challenges and opportunities, and showcase the potential impact of AI-driven optimization in various application domains.

This paper makes significant contributions to the field by providing a comprehensive narrative literature review of machine learning techniques applied to MILP, focusing on learning to optimize methodologies. The discussion extends to applying these techniques in air transportation and mobility, showcasing real-world applications and demonstrating the practical impact of the discussed approaches. The work also analyzes the pipeline as a whole and emphasizes the interactions between different components (Fan et al., 2024).

2 RELATED WORK

Recent research underscores the transformative potential of integrating AI with combinatorial optimization problems, facilitating autonomous learning and decision-making within specific problem sets (Fan et al., 2024).

2.1 Background of Mixed Integer Linear Programming (MILP)

MILP is a versatile mathematical modeling technique extensively employed to depict complex decision-making problems across diverse sectors, including healthcare, supply chain management, energy systems, and finance (Li et al., 2024). Its ability to articulate intricate combinatorial structures and constraints makes it indispensable in academic research and industrial applications (Li et al., 2024). MILP problems involve optimizing a linear objective function subject to a set of linear equality and inequality constraints, where some or all of the decision variables are restricted to be integers. Integer constraints enable accurately modeling problems involving discrete quantities or yes-or-no decisions (Nemhauser & Wolsey, 1999). Due to enhanced solver efficiency and accessibility, MILP has become a cornerstone of operations research (Clautiaux & Ljubić, 2024). A Mixed Integer Linear Program aims to identify the minimum value of a linear function subject to constraints, accommodating both integer and continuous variables (Scavuzzo, Aardal, Lodi, et al., 2024). The formulation of optimization problems as Mixed Integer Linear Programs necessitates considerable mathematical modeling and optimization expertise, thereby constraining accessibility for non-experts. Tackling MILP challenges can be computationally demanding and time-intensive, notably for large-scale instances, attributed to the inherent NP-hardness (Li et al., 2024).

2.2 Traditional Methods for Solving MILP

MILP is a versatile framework employed to model and resolve optimization problems involving continuous and discrete variables, with linear constraints and objective functions. Traditional methods for solving MILP problems encompass a range of exact and heuristic algorithms, each exhibiting distinct strengths and weaknesses (Scavuzzo, Aardal, Lodi, et al., 2024; Scavuzzo, Aardal, & Yorke-Smith, 2024). Branch-and-bound, a classical exact algorithm, systematically explores the solution space by recursively partitioning the problem into smaller subproblems, pruning branches and establishing bounds on the optimal objective value (Fan et al., 2024). Cutting plane methods, another category of exact algorithms, enhances the linear programming relaxation of the MILP problem by iteratively adding valid inequalities (cuts) that eliminate fractional solutions. Heuristic algorithms, including genetic algorithms, simulated annealing, and tabu search, provide approximate solutions within a reasonable time frame, albeit without optimality guarantees. Mathematical programming, particularly Mixed-Integer Linear Programming techniques, is recognized for its effectiveness in addressing scheduling problems, considering factors such as size, complexity, and flexibility in manufacturing processes (Ramin et al., 2018).

2.3 Challenges in Solving MILP Problems

Despite the widespread applicability of MILP, it faces two fundamental limitations: tractability and the requirement for expert formulation (Li et al., 2024). The computational complexity of solving MILP problems, especially large-scale instances, is a major concern due to the inherent NP-hardness. As problem size escalates, the computational resources and time needed to identify optimal solutions can surge exponentially, rendering conventional MILP solvers impractical for real-time applications or large-scale systems. Consequently, there is an ever-growing demand for developing more efficient algorithms and solution methodologies to tackle the computational complexities of MILP. Moreover, expressing real-world problems in the form of Mixed Integer Linear Programs necessitates considerable mathematical modeling and optimization expertise. This poses a challenge for domain experts who may lack the technical proficiency to effectively formulate MILP models. Modern computing architectures offer possibilities for improving MILP-based algorithms (Clautiaux & Ljubić, 2024). Researchers are exploring utilizing GPU architecture, inspired by its success in machine learning and distributed systems, to handle large-scale LPs (Clautiaux & Ljubić, 2024).

2.4 Artificial Intelligence (AI) in Optimization

AI techniques, particularly machine learning, have effectively addressed optimization problems across various domains. Machine learning algorithms can learn from data, discern patterns, and generate predictions, offering complementary tools for improving conventional optimization methodologies (Li et al., 2024). By integrating AI with MILP, it becomes feasible to overcome the limitations of traditional optimization techniques and unlock new possibilities for tackling intricate real-world problems. Machine learning models can learn from historical data to predict optimal or near-optimal solutions, guide search algorithms, and improve decision-making processes. Machine learning excels at distilling insights from data, which is invaluable in optimization contexts

(Pasupuleti et al., 2024). By analyzing historical data, machine learning algorithms can uncover hidden patterns, predict future trends, and inform optimization models, facilitating better decision-making. Furthermore, machine learning algorithms can adapt to changing conditions and dynamically adjust optimization strategies, enhancing the robustness and flexibility of optimization systems.

AI techniques offer complementary tools for improving conventional optimization methodologies. By integrating AI with MILP, it becomes feasible to overcome the limitations of traditional optimization techniques and unlock new possibilities for tackling intricate real-world problems. AI algorithms can be employed to predict optimal solutions, guide search algorithms, and enhance decision-making processes, thereby improving the efficiency and effectiveness of optimization systems (Martínez-Martínez et al., 2020). In addition to machine learning, other techniques have emerged as potent tools for tackling optimization problems across diverse domains. Inspired by natural phenomena or intelligent search strategies, metaheuristics offer versatile frameworks for exploring the solution space and identifying high-quality solutions, especially when traditional optimization algorithms struggle (Iacca et al., 2021). Reinforcement learning is one of the most promising techniques, where an agent learns to make decisions in an environment to maximize a cumulative reward (Singh, 2024). Imitation learning is also applied, where the goal is to learn a policy from expert demonstrations (Fan et al., 2024). Supervised learning algorithms, such as neural networks, can be trained to predict optimal solutions or guide search algorithms based on historical data. Graph Neural Networks and Recurrent Neural Networks are frequently used AI models (Fan et al., 2024).

2.5 Learning to Optimize (L2O) Approaches

Learning to optimize represents a paradigm shift in optimization, wherein machine learning techniques are automatically employed to learn and improve optimization strategies. This approach involves training machine learning models to predict optimal decisions, guide search algorithms, and adapt to changing problem characteristics. The "smart predict-then-optimize" paradigm refines parameter prediction by incorporating feedback from subsequent decision errors (Singh, 2024). Predict-then-optimize methods often struggle to predict parameters, which can significantly affect decision quality accurately. Learning to optimize has been applied to mixed integer non-linear programming and demonstrates strong potential in addressing complex optimization challenges (Fan et al., 2024; Tang et al., 2025). Recent studies emphasize the adaptability of AI models in dynamic environments, showcasing their ability to adjust to changing conditions and enhance overall system performance (Fan et al., 2024).

2.6 Applications of AI in Air Transportation and Mobility

AI has found extensive applications in various facets of air transportation and mobility, including route optimization, scheduling, and predictive maintenance (El Karkouri et al., 2025; Lukic Vujadinovic et al., 2024). For instance, airlines utilize AI-powered systems to optimize flight routes, minimize fuel consumption, and enhance operational efficiency (Najmi et al., 2024). In urban mobility, AI algorithms are employed to optimize traffic flow, manage transportation networks, and facilitate the deployment of autonomous vehicles. AI can predict future demand based on historical data, seasonality, and trends, improving inventory management and reducing stockouts (Singh, 2024). Moreover, AI algorithms optimize routing, scheduling, and resource allocation to enhance efficiency and reduce costs (Singh, 2024).

2.7 Gaps in the Literature

Although existing literature highlights the potential of integrating AI with MILP, several research gaps remain to be addressed. Further research is warranted to explore the application of AI to model formulation and enhancement for specific algorithms, such as the Alternating Direction Method of Multipliers and column generation (Fan et al., 2024). Furthermore, it is crucial to consider ethical considerations, such as protecting user information and integrating informed consent and human autonomy concepts into community engagement programs to promote sustainability in this sector (Mirindi, 2024). The gap is evident as current research often concentrates on enhancing specific algorithms or high-level applications instead of creating integrated frameworks suitable for systems with critical safety concerns (Singh, 2024).

Consequently, practical challenges like data dependence, model interpretability, and transparent decision-making in dynamic environments remain insufficiently addressed (Mirindi, 2024; Singh, 2024). This emphasizes the need to go beyond isolated improvements and build systems where AI's adaptive learning enhances the formal assurances of mathematical optimization. Future work should focus on developing more robust and scalable AI algorithms that can handle the complexity and uncertainty inherent in real-world optimization problems (Mirindi, 2024; Singh, 2024).

3 METHODOLOGY

This research employs a qualitative approach, combining narrative literature review and case studies to investigate the application of AI to solve MILP problems in air transportation and mobility. The review also includes several recent preprints, mainly from arXiv; while acknowledging they have not yet completed the peer-review process, their inclusion is essential for understanding the state-of-the-art in this rapidly evolving field.

3.1 Problem Formulation of MILP

The mathematical formulation of MILP seeks to optimize a linear objective function subject to linear equality and inequality constraints, with some decision variables restricted to integer values. The mathematical notation of the generic MILP problem can be written as:

$$\begin{gathered}\min c^T \mathrm{x} \\ \text{subject to } \mathrm{Ax} \leq \mathrm{b}, \\ \mathrm{x} \in R_{+}^{n1} \times Z_{+}^{n2}\end{gathered}$$

where **x** is the vector of decision variables, **c** is the vector of objective function coefficients, **A** is the matrix of constraint coefficients, and **b** is the vector of constraint bounds.

3.2 Learning to Optimize (L2O) Framework

This work focuses on the application of a specific AI technique, the Learning to Optimize (L2O) framework. In the L2O framework, the main goal is to learn a policy, represented by a function approximator (e.g., a neural network), that can effectively guide the search process in solving MILP problems. The learning to optimize approach enables the development of adaptive optimization strategies that can automatically adjust to the problem characteristics, data distribution, and environmental conditions (Tang et al., 2025).

Two different approaches for L2O application can be adopted: Model-Free and Model-Based (T. Chen et al., 2022). A model-free L2O approach aims to learn a parameterized update rule of optimization without any analytical model update, in general, applying LSTM neural networks and reinforcement learning. Model-based L2O approach combines traditional model-based optimization algorithms with deep learning. Instead of general-purpose LSTMs, this approach models iterative update rules by a learnable architecture inspired by analytic optimization algorithms.

For example, a trained neural network predicts the optimal integer solution from the relaxation linear programming solution (Scavuzzo, Aardal, Lodi, et al., 2024). A complementary approach is to predict the optimal objective value and use it to classify whether the current incumbent is optimal, thus supporting the solver’s transition from the improvement phase to the proving phase (Scavuzzo, Aardal, & Yorke-Smith, 2024). L2O methods can approximate problem solutions with tens of iterations, while classic algorithms require hundreds or thousands of iterations.

3.3 Evaluation Metrics

The performance of the AI-enhanced MILP algorithms can be evaluated using several key metrics, including solution quality (optimality gap), computational time, and scalability.

4 RESULTS

4.1 Case Studies in Air Transportation

4.1.1 Optimizing Flight Schedules

Airlines face the intricate task of optimizing flight schedules to maximize profitability, minimize operational costs, and ensure customer satisfaction. AI algorithms can analyze vast amounts of data, including historical flight data, weather patterns, and aircraft maintenance schedules, to identify optimal flight schedules that minimize delays and maximize aircraft utilization. AI techniques can solve complex optimization problems in air transportation, such as accommodating new flights into existing schedules (Şafak et al., 2019). By integrating AI with MILP models, airlines can make data-driven decisions that significantly improve operational efficiency and profitability (Barnhart & Cohn, 2004).

4.1.2 Resource Allocation at Airports

Airports are complex ecosystems that require efficient allocation of resources, such as gates, runways, and personnel, to ensure smooth operations. AI algorithms can analyze real-time data on flight arrivals and departures, passenger flows, and resource availability to optimize resource allocation and minimize congestion. By optimizing resource allocation, airports can improve passenger experience, reduce delays, and enhance overall operational efficiency (Geske et al., 2024).

4.1.3 Air Traffic Management

AI plays an important role in air traffic control by improving the safety and efficiency of air travel (Abdillah et al., 2024). Using machine learning algorithms, air traffic controllers can make better decisions, and pilots can get help (Demir et al., 2024). AI is beginning to appear in civil aviation, principally via Machine Learning and Deep Learning approaches in various applications, including, for example, flight operations and crewless aerial vehicles, weather prediction, and numerous improvements in air traffic management (Kirwan, 2025).

4.1.4 Crew Pairing and Rostering

For the Crew Pairing Problem (CPP), Pereira et al. (2022) address the trade-off between fast, low-quality solvers and slow, high-quality ones. A machine learning model was used to imitate the decisions of a slow but expert optimization method. This AI-guided strategy produces solutions of nearly the same quality as the expert method (only 0.283% worse on average) while cutting CPU time by approximately 74%.

Following the pairing stage, for the Crew Rostering Problem (CRP), Racette et al. (2025) use a windowing technique. First, a machine learning model generates an initial complete roster. This roster then guides a branch-and-price algorithm that re-optimizes the schedule in smaller, overlapping time windows. The initial solution provides valuable information, enabling the combined approach to be over 10 times faster than the state-of-the-art solver while delivering solutions on average less than 1% from an optimal result.

4.2 Case Studies in Mobility

4.2.1 Smart Transportation Systems

AI-based smart transportation systems have been empirically validated to significantly optimize traffic flow and reduce congestion. In a real-world deployment in Pittsburgh, Pennsylvania, the coordination of autonomous vehicles using AI algorithms led to a 30% reduction in traffic congestion during rush hours (Dikshit et al., 2023). Beyond vehicle coordination, AI-powered traffic signal control systems dynamically adjust signal timings based on real-time data from traffic sensors, GPS devices, and weather forecasts, resulting in documented improvements in average travel times and emissions (Saxena, 2024).

4.2.2 Route Optimization

AI has enabled substantial advances in route optimization for logistics and urban transportation, with direct impacts on delivery times, operational costs, and energy efficiency (Singh, 2024). The main objective is to determine the shortest and most cost-effective paths for vehicles, considering real-world constraints such as traffic dynamics, delivery windows, and vehicle capacity. Large-scale simulation studies demonstrate that AI-driven traffic management strategies can reduce average commute times by up to 25% and decrease fuel consumption by 20% (Dikshit et al., 2023). Complementing these findings, real-world implementations in logistics networks have reported energy cost savings of approximately 10% as a result of more efficient routing and dynamic scheduling optimization (W. Chen et al., 2024a). These outcomes confirm that AI-based route optimization not only improves operational metrics but also contributes to sustainability goals in transportation systems.

4.2.3 Autonomous Vehicles

Autonomous vehicles (AVs) promise to revolutionize urban mobility by providing safe, efficient, and sustainable transportation options through advanced AI integration. These systems employ computer vision, deep learning, and sensor fusion technologies to perceive and navigate complex urban environments while processing real-time data for optimal decision-making (Dikshit et al., 2023; Singh, 2024). Experimental evidence demonstrates significant performance improvements: federated imitation learning frameworks achieve zero collision rates while reducing average jerks by up to 41.37% compared to conventional control methods, enhancing both safety and passenger comfort (Wu et al., 2021).

4.3 Performance of AI Algorithms

The performance of AI algorithms in solving MILP problems depends on several factors, including the size and complexity of the problem, the choice of AI algorithm, and the computational resources available (Gupta et al., 2022). The rise in computational power and the availability of big data have facilitated the practical application of AI techniques to solve complex optimization problems in various domains (Singh, 2024). AI models are trained on extensive traffic data and tested in simulated environments to evaluate their effectiveness (Pillai, 2024).

4.3.1 Comparison with Traditional Methods

AI-enhanced MILP offers several advantages over traditional optimization methods, including handling large-scale problems, adapting to dynamic environments, and learning from experience. Imitation learning yields a version that swiftly predicts expert behavior, thereby correctly tackling the computational project (Singh, 2024). This method performs well in quick decision-making scenarios (Gupta et al., 2022). The effectiveness of traditional traffic management systems is often limited by their inability to adapt to the dynamic nature of urban traffic flow (Pillai, 2024). AI offers a promising alternative because it can analyze real-time traffic data and optimize signal timings adaptively (Pillai, 2024).

4.3.2 Analysis of Solution Quality

The quality of the solutions generated by AI-enhanced MILP algorithms can be evaluated using various metrics, such as optimality gap, solution time, and feasibility. AI techniques in optimization offer several benefits, including the ability to handle complex interactions among variables and constraints, learn from data, and adapt to changing conditions (Singh, 2024). When the interaction inside the constraint matrix is more complicated, simple heuristics are irrelevant, but AI tools are more applicable (Singh, 2024). The implementation of AI, however, is not without challenges. One of the main issues is the interpretability of AI versions (Singh, 2024). In many applications, it is essential to understand how the AI model arrived at a particular solution (Singh, 2024).

4.4 Discussion of Results

The results of this study demonstrate the potential of AI to enhance MILP techniques and improve the efficiency and reliability of air transportation and mobility systems. AI technologies offer the possibility of resolving the intricate optimization problems encountered in transportation and mobility. This involves using machine learning and neural networks to assess and enhance transportation networks, pinpoint potential disruptions, and adapt operations to changing circumstances (Pillai, 2024; Singh, 2024). However, the computational efficiency of AI algorithms is a critical consideration for real-world applications, especially in time-sensitive domains such as air transportation and mobility. AI algorithms are computationally efficient and can provide solutions in real-time (Mirindi, 2024).

5 FINAL CONSIDERATIONS

The application of AI to enhance MILP techniques offers significant benefits for optimizing complex decision-making problems in various domains. AI technologies offer new approaches for solving optimization problems by integrating data-driven insights with mathematical programming techniques (Singh, 2024). AI can enhance optimization algorithms by learning from data, identifying patterns, and adapting to changing conditions (Singh, 2024). Despite the promising results, there are several limitations to the current approach. Integrating AI into transportation systems can transform the industry by addressing critical issues like pollution reduction, improved safety, and traffic congestion alleviation (Mirindi, 2024). AI-driven optimization also extends to optimizing flight routes, scheduling maintenance, and managing passenger flow.

This narrative literature review contributes to the growing literature on the intersection of AI and optimization. Furthermore, while the focus remains on how AI can enhance operations research, the deep roots of machine learning in mathematical optimization are acknowledged (Singh, 2024). Future research directions include exploring the use of AI for model formulation and the enhancement of specific algorithms like column generation, the development of more sophisticated AI algorithms, exploring hybrid AI-optimization approaches, and applying these techniques to other challenging optimization problems (Fan et al., 2024). Among these hybrid approaches, an important direction is the development of interpretable frameworks using model-based L2O to improve core MILP algorithms like branch-and-bound. This progression would advance the L2O field, contributing to the development of reliable AI elements suitable for safety-critical applications.

Further studies are needed to validate the effectiveness of these approaches in real-world settings and to assess their impact on transportation and mobility outcomes. It is vital to focus on improving AI models for increased performance, tackling issues like computational complexity and privacy, and addressing broader ethical considerations such as informed consent and human autonomy, while continuing to innovate in AI to improve transportation systems' economic efficiency and dependability (Mirindi, 2024). It's worth investigating how AI models can provide insights into the decision-making process and how this can lead to more transparent and reliable systems. A distributed smart system with AI algorithms is necessary to address problems in traffic monitoring, congestion prediction, and incident management (Saha, 2019). Using AI capabilities, stakeholders can enhance decision-making processes, optimize resource utilization, and minimize environmental impacts (W. Chen et al., 2024b). AI techniques, including machine learning algorithms, computer vision, and reinforcement learning, are crucial for creating autonomous vehicles and enabling real-time decision-making, object identification, and automation in driving systems (Noviati et al., 2024). Self-driving cars powered by AI offer the potential to dramatically improve road safety, reduce traffic congestion, and increase mobility access (Katiyar et al., 2024).

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