



System Optimization in Industrial Engineering: A Comprehensive Review of Historical Development and Emerging Trends

Optimasi Sistem dalam Teknik Industri: Tinjauan Komprehensif tentang Perkembangan Historis dan Tren Terkini

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Abstrak

Optimasi sistem telah menjadi salah satu pilar utama dalam teknik industri yang berperan penting dalam mendukung pengambilan keputusan dan meningkatkan kinerja sistem yang kompleks. Selama lebih dari satu abad, optimasi berkembang dari teori matematika klasik menjadi suatu kerangka kerja multidisiplin yang mengintegrasikan riset operasi, kecerdasan buatan, pembelajaran mesin, serta teknologi komputasi modern. Artikel ini bertujuan untuk mengulas perkembangan historis, kemajuan terkini, dan prospek masa depan optimasi sistem dalam bidang teknik industri. Penelitian ini menggunakan metode narrative literature review dengan menelaah buku-buku klasik dan artikel ilmiah bereputasi yang diperoleh dari basis data Scopus, Web of Science, IEEE Xplore, dan ScienceDirect. Literatur yang terpilih dianalisis secara tematik untuk menggambarkan perkembangan metode optimasi dari optimasi klasik hingga optimasi cerdas modern. Hasil kajian menunjukkan bahwa optimasi sistem telah bergeser dari pendekatan matematis deterministik menuju sistem pendukung keputusan yang adaptif dan berbasis data sehingga mampu menghadapi kompleksitas permasalahan industri modern. Perkembangan kecerdasan buatan, analitik big data, dan komputasi kuantum semakin memperluas penerapan optimasi pada berbagai bidang, seperti manufaktur, logistik, layanan kesehatan, energi, dan industri cerdas. Kajian ini menyimpulkan bahwa penelitian di masa depan perlu berfokus pada integrasi optimasi dengan teknologi digital mutakhir guna menghasilkan kerangka kerja pengambilan keputusan yang lebih cerdas, skalabel, dan berkelanjutan dalam teknik industri..

Kata kunci: Kecerdasan Buatan, Komputasi Kuantum, Optimasi Sistem

Abstract

System optimization has become one of the fundamental pillars of industrial engineering, supporting effective decision-making and improving the performance of complex systems. Over the past century, optimization has evolved from classical mathematical theories into an interdisciplinary framework that integrates operations research, artificial intelligence, machine learning, and advanced computational technologies. This study aims to review the historical evolution, current developments, and future prospects of system optimization in industrial engineering. A narrative literature review was conducted by examining seminal books and peer-reviewed articles indexed in major scientific databases, including Scopus, Web of Science, IEEE Xplore, and ScienceDirect. The reviewed literature was analyzed thematically to identify the progression of optimization methodologies from classical optimization to modern intelligent optimization. The findings indicate that system optimization has shifted from deterministic mathematical modeling toward adaptive and data-driven decision-support systems capable of addressing increasingly complex industrial challenges. Recent advances in artificial intelligence, big data analytics, and quantum computing have significantly expanded the scope and capability of optimization techniques across



manufacturing, logistics, healthcare, energy, and smart industrial systems. The review concludes that future research should focus on integrating optimization with emerging digital technologies to develop more intelligent, scalable, and sustainable decision-support frameworks for industrial engineering.

Keywords: Artificial Intelligence, Industrial Engineering, Literature Review

INTRODUCTION

Optimization has traditionally been understood as the process of identifying the best feasible solution by minimizing or maximizing an objective function within a defined set of constraints. Commonly formulated as a mathematical programming problem, optimization seeks an optimal decision over a feasible solution space through rigorous analytical procedures. Because of its strong mathematical foundations, optimization has historically been regarded as a branch of applied mathematics. Over time, however, its role has expanded substantially. Within industrial engineering, optimization is no longer viewed merely as a mathematical technique but as a comprehensive decision-support framework for designing, managing, and improving complex systems (Hillier & Lieberman, 2021; Bertsimas & Tsitsiklis, 1997).

The evolution of industrial systems has transformed optimization into one of the fundamental pillars of industrial engineering. Rather than focusing exclusively on numerical solution techniques, contemporary system optimization integrates mathematical modeling, systems thinking, operational decision-making, and computational intelligence to address increasingly complex organizational and societal challenges (Bertsimas & Dunn, 2019; Powell, 2022). Consequently, optimization has become indispensable for improving efficiency, allocating limited resources, enhancing productivity, and supporting strategic decision-making across manufacturing, healthcare, transportation, logistics, and service industries (Pinedo, 2022).

The historical development of system optimization can be understood through several successive stages. Early research concentrated primarily on developing analytical methods capable of solving mathematically well-defined optimization problems. As industrial systems became increasingly interconnected, optimization evolved into a systems-oriented discipline in which interactions among multiple components, uncertainty, and managerial decision-making became integral parts of the analytical framework. More recently, advances in artificial intelligence, machine learning, and data-driven analytics have expanded optimization research toward dynamic, stochastic, and multidisciplinary environments that require adaptive and intelligent decision-support systems (Powell, 2022; Bertsimas & Dunn, 2019).

Industrial engineering fundamentally adopts a systems perspective in which organizations are viewed as integrated networks of people, machines, materials, information, and technologies. From this perspective, overall system performance is prioritized over the isolated optimization of individual components. This philosophy originated from the principles of scientific management, introduced by Frederick W. Taylor, who argued that organizational productivity should be achieved through systematic analysis, standardized work procedures, scientific experimentation, and evidence-based managerial decisions rather than intuition alone (Taylor, 1911). Although industrial engineering has evolved considerably since Taylor's era, the underlying principle of optimizing integrated systems remains central to the discipline (Hillier & Lieberman, 2021).



Management science provides the methodological foundation through which these optimization principles are implemented. In particular, system optimization represents a prescriptive analytical approach that transforms real-world decision problems into mathematical models, evaluates alternative solutions, and identifies decisions that maximize overall system performance under various operational constraints (Winston & Goldberg, 2004; Powell, 2022). Unlike classical optimization, which primarily focuses on algorithmic efficiency and mathematical properties, system optimization incorporates managerial judgment, system boundaries, organizational objectives, and stakeholder interactions into the optimization process. Consequently, optimization has become a strategic decision-support methodology applicable to manufacturing systems, supply chains, healthcare operations, transportation networks, energy systems, and public-sector planning.

The emergence of big data, artificial intelligence (AI), and machine learning has further accelerated the evolution of system optimization. Modern industrial systems continuously generate enormous volumes of heterogeneous data that require sophisticated optimization models capable of supporting predictive, adaptive, and autonomous decision-making. The integration of optimization with AI enables organizations to improve operational efficiency while responding dynamically to uncertain and rapidly changing environments (Jordan & Mitchell, 2015; Goodfellow et al., 2016; Russell & Norvig, 2021). Consequently, optimization research has increasingly focused on scalable algorithms capable of solving large-scale problems in real time while maintaining computational efficiency and solution quality.

Looking ahead, the next frontier of system optimization will likely be shaped by emerging computational paradigms, particularly quantum computing. Unlike conventional digital computing, quantum computing has the potential to solve certain classes of combinatorial optimization problems exponentially faster by exploiting quantum superposition and entanglement (Montanaro, 2016; Gill et al., 2024). Although practical large-scale implementation remains under development, quantum optimization is expected to redefine the computational capabilities available for solving highly complex industrial decision problems.

Accordingly, this paper revisits the historical evolution of system optimization, examines its current methodological developments and industrial applications, and discusses future research directions within the context of intelligent computing technologies. Rather than providing a conventional literature review, this study seeks to establish a conceptual framework that supports future theoretical development and interdisciplinary research in industrial engineering.

METHOD

This study employed a qualitative historical review combined with a narrative literature review to examine the evolution of system optimization in industrial engineering. Unlike systematic reviews that follow rigid protocols for article selection and statistical synthesis, narrative reviews aim to provide a comprehensive conceptual understanding of the historical development, theoretical foundations, and emerging research directions within a particular discipline (Grant & Booth, 2009).

The review was conducted through four sequential stages. First, seminal publications that have significantly influenced the development of optimization theory were identified. These included foundational works on classical optimization, linear programming, nonlinear optimization, operations research, systems engineering, and computational optimization. Landmark contributions



by Fermat, Newton, Euler, Lagrange, Dantzig, and subsequent researchers were examined to establish the historical trajectory of optimization methodologies.

Second, contemporary literature was collected from internationally recognized scientific databases, including Scopus, Web of Science, IEEE Xplore, and ScienceDirect. Priority was given to peer-reviewed journal articles, academic books, and review papers published in high-impact journals related to industrial engineering, operations research, optimization, artificial intelligence, and quantum computing. Recent publications from approximately the last decade were emphasized to capture current developments and emerging research trends while retaining classical references that have shaped the theoretical foundations of the field.

Third, the selected literature was analyzed using thematic analysis. Studies were categorized according to major developmental phases of optimization, including classical optimization, modern optimization, and contemporary optimization. Within each category, the literature was examined to identify methodological advancements, computational innovations, industrial applications, and theoretical contributions. This thematic organization enabled a chronological interpretation of how optimization has evolved from a mathematical discipline into a comprehensive decision-support framework for complex systems.

Finally, a conceptual synthesis was conducted to integrate historical perspectives with current technological developments. Particular attention was given to the convergence of optimization with artificial intelligence, machine learning, big data analytics, and quantum computing. Rather than quantitatively comparing previous studies, this synthesis aimed to construct an integrated conceptual framework that illustrates the changing role of system optimization in industrial engineering and identifies promising directions for future research.

The methodological approach adopted in this study follows established recommendations for conducting high-quality narrative reviews by emphasizing transparency in literature selection, conceptual integration, and critical interpretation of existing knowledge rather than statistical aggregation of empirical findings (Baumeister & Leary, 1997; Grant & Booth, 2009; Snyder, 2019).

RESULTS AND DISCUSSIONS

1. Results

Historical Evolution of System Optimization

The literature reviewed indicates that the evolution of system optimization can be classified into three major developmental phases: classical optimization, modern optimization, and contemporary optimization. Classical optimization was primarily concerned with establishing mathematical principles for determining optimal solutions. Early contributions by Fermat, Newton, Euler, and Lagrange introduced the mathematical foundations of unconstrained and constrained optimization, including differential calculus, variational methods, and the Lagrange multiplier technique (Nocedal & Wright, 2006; Boyd & Vandenberghe, 2004).

A major transition occurred following the introduction of linear programming and the simplex algorithm by Dantzig in 1947. This innovation demonstrated that optimization could be systematically applied to solve complex planning and resource allocation problems, thereby



transforming optimization into a practical decision-support methodology for industrial and military applications (Dantzig, 1963).

Subsequent advances in digital computing expanded the applicability of optimization from relatively small mathematical models to increasingly complex industrial systems. During this period, optimization techniques evolved to include nonlinear programming, integer programming, stochastic optimization, dynamic programming, and network optimization, allowing researchers and practitioners to address more realistic engineering problems (Hillier & Lieberman, 2021).

Current Developments in System Optimization

The reviewed studies reveal that contemporary optimization has moved beyond deterministic mathematical modeling toward intelligent and adaptive decision-making. Modern optimization increasingly integrates artificial intelligence, machine learning, simulation, and data analytics to improve decision quality in uncertain and dynamic environments (Powell, 2022).

Another significant finding is the widespread application of optimization across industrial sectors. Optimization methodologies are currently employed in production scheduling, supply chain management, healthcare systems, transportation networks, energy management, smart manufacturing, and logistics. The availability of large-scale datasets has further accelerated the development of optimization algorithms capable of processing high-dimensional decision problems in real time (Bertsimas & Dunn, 2019).

Emerging Trends

The literature also identifies quantum computing as one of the most promising directions for future optimization research. Although current quantum hardware remains limited, several studies suggest that quantum optimization algorithms may substantially improve the computational efficiency of solving combinatorial optimization problems that are computationally expensive for classical computers (Montanaro, 2016; Gill et al., 2024).

Overall, the reviewed literature demonstrates that system optimization has evolved from a mathematical problem-solving technique into an interdisciplinary framework supporting intelligent decision-making in increasingly complex industrial environments.

2. Discussion

The findings of this review highlight that the evolution of system optimization has consistently been driven by technological advancement and increasing system complexity. While early optimization research focused primarily on mathematical theory, subsequent developments shifted attention toward solving practical decision problems encountered in industrial systems. This transformation reflects the growing recognition that optimization should support not only computational efficiency but also effective managerial decision-making.

Another important observation concerns the changing role of industrial engineering. Classical optimization emphasized identifying mathematically optimal solutions, whereas contemporary system optimization incorporates uncertainty, multiple objectives, and interactions among interconnected system components. Consequently, optimization has become



an essential element of systems engineering, operations research, and intelligent decision-support systems (Hillier & Lieberman, 2021; Powell, 2022).

The integration of optimization with artificial intelligence represents another significant paradigm shift. Machine learning enhances optimization by providing predictive capabilities, whereas optimization algorithms determine the most effective actions based on those predictions. This complementary relationship enables organizations to respond more effectively to dynamic operating environments characterized by uncertainty and rapidly changing information (Bertsimas & Dunn, 2019; Jordan & Mitchell, 2015).

Furthermore, the increasing availability of big data has fundamentally altered optimization research. Rather than relying exclusively on predefined mathematical models, contemporary optimization increasingly incorporates data-driven approaches capable of continuously updating decisions using real-time information. This evolution has broadened optimization applications from traditional manufacturing systems to healthcare, smart cities, autonomous transportation, and sustainable energy systems.

The review also suggests that quantum computing may represent the next major milestone in optimization research. Although practical implementation remains constrained by technological limitations, quantum algorithms have demonstrated considerable theoretical potential for solving large-scale combinatorial optimization problems more efficiently than conventional computational methods (Montanaro, 2016). Future research should therefore investigate hybrid optimization frameworks that integrate classical algorithms, artificial intelligence, and quantum computing to address increasingly complex industrial systems.

Overall, this review demonstrates that system optimization has evolved into an interdisciplinary decision-support framework that integrates mathematical modeling, computational intelligence, and systems thinking. Future advances in industrial engineering will likely depend on the successful integration of these technologies to improve the efficiency, adaptability, and resilience of complex socio-technical systems.

CONCLUSION

This review has examined the historical evolution, current developments, and future prospects of system optimization within the field of industrial engineering. The findings indicate that optimization has progressed from a mathematically oriented discipline concerned primarily with identifying optimal solutions for well-defined problems into a comprehensive decision-support framework capable of addressing increasingly complex industrial and societal systems. Throughout its historical development, optimization has continuously evolved in response to advances in mathematical theory, computational technologies, and the growing complexity of real-world decision environments.

The review further demonstrates that system optimization has become one of the fundamental pillars of industrial engineering. While early optimization research focused on analytical models and algorithmic efficiency, contemporary optimization increasingly integrates systems thinking, operations research, artificial intelligence, machine learning, and big data analytics to support adaptive and intelligent decision-making. This interdisciplinary evolution has significantly expanded the applicability of optimization across diverse sectors, including



manufacturing, healthcare, transportation, logistics, energy systems, and smart industries.

Another important finding is that recent technological advances are reshaping the future direction of optimization research. The convergence of optimization with artificial intelligence enables more predictive and autonomous decision-making, whereas emerging computational paradigms such as quantum computing present new opportunities for solving large-scale combinatorial optimization problems that remain computationally challenging for classical algorithms. Although these technologies are still developing, they are expected to transform the capabilities of future optimization systems and broaden the scope of industrial engineering research.

Overall, this review highlights that the future of system optimization lies not only in developing faster algorithms but also in creating integrated decision-support frameworks capable of managing uncertainty, complexity, and real-time system dynamics. Continued collaboration among industrial engineering, computer science, operations research, and artificial intelligence will therefore be essential for advancing optimization methodologies that are both computationally efficient and practically relevant in increasingly digital and intelligent industrial environments.

SUGGESTIONS

Based on the findings of this review, several recommendations are proposed to guide future research and practical implementation of system optimization.

First, future research should focus on developing hybrid optimization frameworks that integrate mathematical optimization, machine learning, artificial intelligence, and simulation techniques. Such integration is expected to improve decision quality in dynamic and data-intensive environments while enhancing the adaptability of optimization models to rapidly changing industrial conditions.

Second, greater attention should be given to the development of optimization methodologies capable of processing large-scale, real-time decision problems. As industrial systems continue to generate massive volumes of data through digital technologies and the Internet of Things (IoT), optimization algorithms must become increasingly scalable, computationally efficient, and responsive to continuously changing information.

Third, researchers are encouraged to investigate the practical potential of quantum computing for industrial optimization. Although current quantum technologies remain at an early stage of development, future studies should explore hybrid classical–quantum optimization approaches, benchmark their computational performance, and evaluate their applicability to complex industrial engineering problems.

Fourth, future studies should expand optimization research beyond algorithmic performance by incorporating broader organizational and societal objectives, including sustainability, resilience, explainability, and human-centered decision-making. Such perspectives will ensure that optimization contributes not only to operational efficiency but also to long-term organizational competitiveness and sustainable development.

Finally, stronger interdisciplinary collaboration among researchers in industrial engineering, operations research, computer science, artificial intelligence, and data science is recommended. Collaborative research will facilitate the development of next-generation optimization



methodologies capable of addressing increasingly complex socio-technical systems while supporting the digital transformation of modern industries.

For Future Researchers

Future studies may involve a larger number of participants and different study programs to obtain more comprehensive and generalizable results. Researchers are also encouraged to use experimental or mixed-method designs to examine not only students' perceptions but also the impact of AhaSlides on students' learning achievement, motivation, and communication skills.

For Curriculum Development

The integration of interactive digital media such as AhaSlides should be considered as part of curriculum innovation. This will support the development of more student-centered, engaging, and technology-enhanced learning environments.

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