Artificial Intelligence and Quantum Computing in Data-Driven Industrial Systems

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Abstract: Modern industrial environments are evolving into data-intensive cyber-physical systems that require robust computational frameworks for performance prediction and optimization. While existing literature has addressed developments in statistical methods, artificial intelligence, and quantum computing individually, there remains a lack of systematic reviews examining the integrated evolution and data processing capabilities of these three paradigms. This review addresses the need to clarify the capabilities, limitations, and application domains of each approach to enable engineers to select appropriate data-driven methodologies for specific optimization challenges. In this review, we traced the historical development of optimization methodologies from design of experiments and response surface methodology through neural networks and generative models to variational quantum algorithms, presented chronological development tables documenting key milestones in each paradigm, and analyzed industrial implementation cases including conversion rate increases and emission reductions. The analysis reveals that statistical methods exhibit unique strengths in systematic data analysis, AI in complex pattern recognition, and quantum computing in high-complexity simulation, with their hybrid integration providing optimal performance. This study provides significance in offering a comprehensive framework necessary for connected industries to strategically deploy multi-paradigm optimization strategies within integrated network environments to achieve sustainability goals while maintaining global competitiveness.

Keywords: Industrial systems optimization, Artificial intelligence, Quantum computing, Statistical methods, Cyber-Physical systems.

1. INTRODUCTION

The advancement of communication engineering and digital transformation has turned traditional manufacturing facilities into sophisticated cyber-physical systems (CPS) that generates vast amounts of operational data [1]. In this context, computational intelligence determines competitive advantage and operational excellence. Specifically, process industries produce essential materials through complex dynamic systems that demand precise optimization of multivariate control parameters including temperature and pressure conditions under strict constraints [2]. The pursuit of optimal operating conditions has driven decades of methodological innovation, progressing from early statistical quality control methods through sophisticated machine learning algorithms to emerging quantum computing approaches that promise to solve previously high-complexity simulation challenges [3].

This review examines the evolution of optimization methodologies for process industries across three computational paradigms. Statistical methods established foundational frameworks for systematic experimentation and quality control beginning in the 1920s, with response surface methodology and multivariate statistical process control becoming standard industrial practice by the late 20th century [4-6]. Artificial intelligence techniques emerged as powerful alternatives following the deep learning revolution of the 2010s, enabling data-driven process modeling, autonomous process optimization, and intelligent control systems [7-9]. Quantum computing represents the newest frontier, offering theoretical advantages for micro-scale simulations that could fundamentally transform material design and system behavior analysis [3, 7].

The industrial significance of these optimization approaches extends beyond incremental efficiency improvements. Energy-intensive industrial sectors consume approximately 10 percent of global energy and produce substantial greenhouse gas emissions. Improved optimization methods directly impact sustainability outcomes while generating substantial economic value. Recent implementations of AI-driven control systems have demonstrated significant improvements in conversion rates alongside substantial reductions in greenhouse gas emissions. Understanding the capabilities, limitations, and appropriate application domains of statistical, AI, and

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Received on 30-12-2025 Accepted on 05-02-2026 Published on 02-03-2026

E-ISSN: 2979-1081/26

quantum computing approaches enables engineers to select optimal data-driven methodologies for specific optimization challenges.

2. STATISTICAL METHODS IN INDUSTRIAL OPTIMIZATION

The foundation of modern industrial process optimization rests upon statistical principles developed during the early twentieth century. Control charts introduced in 1924 established statistical process control as a discipline that distinguishes common cause variation inherent to manufacturing systems from special cause variation requiring corrective intervention [10]. This innovation enabled systematic quality monitoring across diverse manufacturing contexts including complex production facilities. Contemporary manufacturers employ Shewhart charts, cumulative sum charts, and exponentially weighted moving average charts for real-time monitoring of system outputs, quality metrics, and process stability indicators. [11].

Design of experiments methodology transformed experimental practice through formalization of randomization, replication, and blocking principles that underpin modern experimental optimization [11]. Analysis of variance provided systems engineers with rigorous statistical frameworks for evaluating the effects of multiple process variables simultaneously. Factorial experimental designs enable systematic investigation of temperature, pressure, and critical input variable effects on system efficiency and output quality without requiring prohibitively large numbers of experiments [12]. These approaches remain fundamental to process development in high-precision manufacturing where regulatory requirements demand demonstrated understanding of process parameter effects.

Response surface methodology introduced in 1951 revolutionized process parameter optimization through sequential experimental approaches that guide researchers toward optimal operating regions [13]. The methodology employs steepest ascent methods followed by detailed exploration using central composite or Box-Behnken designs [14]. Process engineers routinely apply response surface methodology to multivariate dynamic processes where temperature, cycle time, and input rates require simultaneous optimization [15, 16]. Advanced product development relies extensively on these methods for optimizing delivery systems and component ratios [14]. The integration of designed experiments with polynomial regression models enables prediction of optimal conditions while quantifying uncertainty in the estimated optimum.

Multivariate statistical methods expanded optimization capabilities for processes generating high-dimensional measurement data [17]. Principal component analysis reduces complex datasets to interpretable latent variable representations that capture primary modes of process variation. Multiway principal component analysis and partial least squares methods developed during the 1980s and 1990s specifically addressed batch manufacturing monitoring applications [18]. The 1995 demonstration of multivariate statistical process control for industrial batch operations established approaches now standard throughout advanced manufacturing sectors [18].

Model predictive control emerged from large-scale industrial applications during the 1970s as process engineers sought to operate closer to economic constraints while maintaining safe and stable operation [19]. IDCOM and Dynamic Matrix Control algorithms developed for complex dynamic units demonstrated the value of explicit constraint handling in optimization-based control [20]. By 2003, documentation showed more than 4,500 industrial model predictive control implementations concentrated in energy and materials processing industries [21]. Modern implementations incorporate statistical elements including uncertainty quantification and constraint handling that enable operation near optimal boundaries despite disturbances and model uncertainty. In practice, advanced statistical control strategies such as MPC have demonstrated energy savings of 5–15% in large-scale subsystems and substantial reductions in energy consumption by stabilizing process variability closer to theoretical efficiency limits [21].

Bayesian optimization represents a recent statistical advancement that has gained substantial traction for black-box function optimization since 2010 [22]. These methods employ Gaussian process surrogate models with acquisition functions that balance exploration of uncertain regions against exploitation of promising operating conditions [22]. Demonstrations in 2021 showed that Bayesian optimization outperformed human experts in identifying optimal operating conditions. Purpose-built algorithms address complex optimization challenges through handling of discrete and continuous variables simultaneously [23]. Sequential experimental strategies guided by probabilistic models enable sample-efficient optimization when experiments are expensive or time-consuming. Furthermore, rigorous experimental designs provide structured, high-quality datasets essential for training robust artificial intelligence models in the subsequent paradigm.

Table 1: Chronological Development of Statistical Methods in Industrial Systems Optimization

Year	Development	Significance for Industrial Systems
1924	Control charts for statistical process control	Systematic quality monitoring for manufacturing [24]
1925	Analysis of variance methodology	Framework for evaluating process variable effects [25]
1935	Design of experiments principles	Efficient experimental strategies for optimization [14]
1960	Box-Behnken experimental designs	Three-level designs for process optimization [14]
1978	IDCOM model predictive control	Constrained dynamic optimization for refineries [20]
1986	Six Sigma quality methodology	Structured statistical improvement framework [26]
1991	Multivariate process monitoring via PCA	Fault detection for complex chemical processes [4, 11]
2012	Gaussian process Bayesian optimization	Sample-efficient optimization framework [27]

3. AI IN INDUSTRIAL OPTIMIZATION

Artificial intelligence methods for industrial system optimization experienced transformation following advances in deep learning architectures and computational hardware during the period from 2015 to 2025 [28]. Bibliometric data indicate that AI-related industrial publications increased exponentially beginning in 2015, with annual machine learning publications in manufacturing sectors exceeding 20,000 by 2022 [29]. This growth reflects both algorithmic advances and expanding availability of industrial process data that enables training sophisticated predictive models [30].

Neural network architectures for system state prediction and process outcome forecasting matured substantially during this decade [31]. Graph convolutional neural networks and message passing neural networks achieve state-of-the-art performance on structural property benchmarks, commonly employed for evaluating inter-component interactions and energy states [31]. Transformer architectures introduced in 2019 achieved greater than 90 percent accuracy for forward process prediction, demonstrating that transformer models originally developed for natural language processing transfer effectively to industrial sequence representations using symbolic encodings [32].

Generative models for material and system design represent a transformative application area that enables inverse design of components with desired properties [33]. Variational autoencoders map structural configurations to continuous latent spaces where optimization algorithms can search for parameters satisfying property constraints [34]. Generative adversarial networks and recurrent neural networks provide alternative generative frameworks [35]. Advanced platforms combining multiple generative models demonstrated practical impact through design of novel high-performance materials with optimized physical properties.

Reinforcement learning approaches for process control emerged as an active research direction with industrial potential [36]. Spielberg *et al*. covered reinforcement learning applications for process control while demonstrations of deep reinforcement learning for complex processes introduced concepts of self-driving systems [37]. These methods learn control policies directly from process interaction without requiring explicit dynamic models, potentially addressing challenges posed by highly nonlinear industrial systems [36]. Control-informed reinforcement learning integrates proportional-integral-derivative components with deep reinforcement architectures to improve sample efficiency and constraint handling [38].

Physics-informed neural networks (PINN) address fundamental limitations of purely data-driven approaches by encoding governing equations directly into network architectures or loss functions. The Stiff-PINN algorithm demonstrated physics-informed approaches for stiff system dynamics using quasi-steady-state approximations [39]. Industrial dynamic systems frequently exhibit stiffness arising from disparate timescales of elementary processes, creating challenges that standard neural network architectures struggle to capture. Physics-informed approaches improve generalization beyond training data distributions and reduce data requirements by leveraging physical conservation principles and system constraints [39]. Hybrid models combining mechanistic first-principles components with neural network approximations for difficult-to-model phenomena have emerged as promising frameworks for digital twins of industrial processes [39].

Large language models (LLMs) entered the industrial process domain following demonstrations that fine-tuned models achieve performance comparable to conventional machine learning approaches [40]. Agent-based frameworks combine LLMs with expert-designed tools enabling autonomous planning, condition recommendation, and safety assessment [41]. These developments suggest that foundation models may increasingly serve as interfaces for system optimization, enabling natural language interaction with complex computational pipelines.

Autonomous production platforms integrate AI with robotic systems to execute complete experimental campaigns without human intervention [42]. Automated platforms autonomously synthesized complex compounds while plug-and-play flow systems automatically produced various target materials. Cloud-based autonomous laboratory capabilities with AI-driven planning demonstrate integration of strategic algorithms with physical execution that may fundamentally transform industrial development workflows [42].

Industrial adoption of AI for process optimization progressed substantially at major manufacturers. Leading industrial firms implemented AI-powered predictive maintenance across manufacturing facilities achieving 15 percent reduction in unplanned downtime [44]. Transparent AI-assisted processes achieved efficiency increases of over 4 percent, production yield improvements, and significant emission reductions [45]. These implementations validate the practical value of machine learning approaches for industrial system optimization. Looking forward, these AI architectures are increasingly applied to optimize quantum circuits, serving as a bridge to the quantum computing era.

4. QUANTUM COMPUTING IN INDUSTRIAL OPTIMIZATION

Quantum computing offers theoretical computational advantages for simulating high-dimensional quantum systems that govern complex industrial dynamics and operational efficiencies [3, 7]. Classical computers face exponential scaling challenges when representing quantum mechanical states for systems beyond a certain complexity threshold [46]. Quantum computers may naturally represent these states using entangled qubit systems, potentially enabling accurate simulation of critical transition points and interaction networks that determine system performance [47]. The decade from 2015 to 2025 established foundational algorithms, demonstrated proof-of-concept calculations, and clarified resource requirements for industrially relevant applications.

The Variational Quantum Eigensolver (VQE) introduced in 2014 provided a hybrid quantum-classical framework suitable for near-term quantum hardware. VQE employs parameterized quantum circuits to prepare trial states that classical optimizers iteratively improve to minimize cost functions [48]. This approach enabled quantum simulation on noisy intermediate-scale quantum devices by accepting hardware limitations through variational flexibility. The first scalable quantum simulation using superconducting qubits and VQE in 2016 represented a landmark demonstration on universal digital quantum computers [49].

Computational complexity benchmarks expanded in 2017 through simulations of multi-variable systems using hardware-efficient VQE ansatz [50]. Published results demonstrated that careful circuit design could extract meaningful systematic information despite hardware noise. The same year, proposals identified large-scale correlated systems as the benchmark problem for quantum simulation [51]. These high-complexity benchmarks represent energy-intensive industrial processes that consume significant global energy. Understanding these underlying system dynamics could enable designs that dramatically reduce industrial energy requirements.

Initial resource estimates for large-scale system simulations appeared daunting, with early projections requiring approximately 100 logical qubits operating for

Table 2: Chronological Development of AI in Industrial Systems Optimization from 2016 to 2024

Year	Development	Significance for Industrial Systems
2016	Neural networks for outcome prediction	High recovery rate on system benchmarks [29]
2018	Inverse system design frameworks	Established generative model approaches [43]
2019	Transformer architecture for sequences	High accuracy in process prediction [32]
2019	Reinforcement learning for process control	Model-free control policy learning [36]
2021	Stiff-PINN for system dynamics	Physics-informed networks for stiff systems [39]
2024	LLM-based agent frameworks	LLM integration with specialized tools [41]
2024	Generative AI for process operations	Foundation models across industrial applications [35]

extended durations. Since thousands of physical qubits are typically needed to create a single logical qubit, this translated to a requirement of millions of physical qubits. Algorithmic improvements have steadily reduced these requirements [52]. Publications in 2021 demonstrated that advanced tensor methods could drastically reduce resource requirements with reasonable runtimes [52, 53]. Alternative qubit architectures estimate that distinct error-correction approaches could address the problem. These improvements illustrate how algorithm innovation continues closing the gap between current hardware and practical industrial applications.

The Quantum Approximate Optimization Algorithm (QAOA) addresses combinatorial optimization problems relevant to network scheduling and supply chain logistics [54]. QAOA alternates between cost function evaluation and mixer operations to search for optimal solutions to problems including maximum cut, traveling salesman, and resource allocation. Industrial facilities face complex scheduling challenges involving multi-stage operations and dynamic routing that QAOA may eventually address more effectively than classical heuristics [55]. Quantum annealing provides an alternative optimization approach commercialized by D-Wave Systems with systems exceeding 5,000 qubits [56].

A significant milestone occurred in August 2020 through the first quantum simulation of a dynamic state transition. Modeling of system reconfiguration and multi-body interactions used the 53-qubit Sycamore processor [57]. This demonstration of fundamental state configuration calculations established that quantum hardware could address dynamic evolution rather than just static properties. Subsequent simulations using trapped-ion architecture demonstrated the largest system simulations at that time [58].

Error correction represents the critical challenge determining when quantum computers will achieve practical advantage for industrial applications. The Willow chip demonstrated a breakthrough in late 2024 by showing that adding more qubits reduced overall error rates [59]. This reversal of error scaling trends suggests that fault-tolerant quantum computing may be achievable within the coming decade. Multiple companies including IBM, Quantinuum, QuEra, and IonQ announced error correction advances throughout 2024 and 2025 [60]. Partially fault-tolerant QAOA demonstrations using error detection codes point toward near-term utility for optimization problems.

Quantum-centric supercomputing demonstrated in 2024 combined quantum processing units with classical supercomputer nodes [61]. Using sample-based quantum diagonalization algorithms, researchers simulated complex state decoupling and energy transfer dynamics relevant to advanced engineering systems [62]. These hybrid approaches leveraging both quantum and classical computing resources may provide practical advantages before fully fault-tolerant systems become available.

Major technology and industrial conglomerates established quantum computing partnerships anticipating eventual practical advantages. Demonstrations of quantum-enhanced machine learning for manufacturing quality prediction achieved 93 percent accuracy compared to 74 percent with classical methods alone [66]. Partnerships between industrial leaders and quantum computing providers target complex electronic structure calculations and material synthesis optimization. Collaborations between energy companies and quantum computing

Table 3: Chronological Development of Quantum Computing in Industrial Systems Optimization from 2015 to 2025

Year	Development	Significance for Industrial Processes
2014	Variational Quantum Eigensolver	Hybrid quantum-classical algorithm for system ground states [48]
2014	Quantum Approximate Optimization Algorithm	Combinatorial optimization framework [63]
2016	Scalable system simulation	VQE demonstration on superconducting qubits [49]
2017	Hardware-efficient simulations	Hardware-efficient ansatz validation [50]
2017	Large-scale benchmark estimation	Benchmark problem for quantum simulation [51, 52]
2019	ADAPT-VQE algorithm	Adaptive variational approach [64]
2020	Dynamic system simulations	Dynamic reconfiguration on Sycamore processor [53]
2021	Reduced resource requirements	Tensor hypercontraction algorithm improvements [65]
2024	Quantum error correction breakthrough	Error reduction with increasing qubit count [54]
2024	Quantum-centric supercomputing	Hybrid simulation of complex transfer systems [62]

firms address process system optimization. Industry estimates suggest quantum computing could create substantial economic value in high-tech domains by 2035 [67].

Realistic timelines for quantum advantages in industrial applications remain subjects of expert debate. Projections suggest fault-tolerant quantum computers with millions of qubits by 2030, enabling large-scale relevant simulations [68]. Alternative estimates suggest another 20 years may be required for truly revolutionary impacts on the field. Conservative projections estimate 15 to 30 years before broadly useful quantum computers become available [69]. Near-term value exists in hybrid classical-quantum optimization for logistics and scheduling problems where demonstrations already show commercial potential.

5. CONCLUSION

The optimization of complex industrial systems has progressed through distinct computational paradigms that each contribute essential capabilities to modern manufacturing operations. Statistical methods including design of experiments, response surface methodology, and multivariate process monitoring provide rigorous frameworks for systematic experimentation and quality control that remain fundamental to regulatory compliance and continuous improvement initiatives. These approaches excel when process relationships are reasonably linear and experiments are relatively inexpensive to conduct.

Artificial intelligence methods have demonstrated capabilities for pattern recognition in complex operational data, generative design of components with desired properties, and learning control policies directly from process data. The period from 2015 to 2025 transformed AI in manufacturing from academic exploration to industrial deployment, with major enterprises reporting performance improvements. Physics-informed neural networks address limitations of purely data-driven approaches by encoding conservation principles and system constraints. Large language models offer natural language interfaces for interacting with sophisticated computational engineering workflows.

Quantum computing remains in an earlier developmental stage but has established potential advantages for high-dimensional simulation problems that govern system dynamics and efficiency drivers. VQE and QAOA algorithms demonstrated on near-term hardware provide foundations for future fault-tolerant implementations. High-complexity benchmark problems represent both a grand challenge and a value proposition given the energy requirements of large-scale industrial processes. Error correction breakthroughs in 2024 and 2025 accelerated timelines for achieving practical quantum advantage.

System engineers must recognize that these methodologies complement rather than replace each other. Statistical experimental design remains essential not only for generating high-quality training data for machine learning models but also for systematically exploring new variable spaces where historical data is scarce. While deep learning models excel at interpolation within known data ranges, they are inherently vulnerable in extrapolation; thus, statistical methods serve as a critical guide for populating these unexplored regions to ensure robust model performance. AI surrogate models can then accelerate optimization when combined with Bayesian search strategies. Quantum computing may eventually provide ground-truth states that serve as training data or validation benchmarks for classical machine learning potential.

Hybrid approaches integrating strengths across paradigms will likely prove most effective for industrial applications. Future research directions include development of transfer learning methods that leverage process data across related industrial systems, integration of autonomous laboratory platforms with AI planning algorithms for self-driving development, and continued algorithm and hardware improvements bringing quantum simulation advantages closer to practical realization. The manufacturing industry faces sustainability challenges requiring efficiency improvements and process innovations. Advanced computational optimization methods across all three paradigms discussed here will prove essential for meeting these challenges while maintaining economic competitiveness in global markets.

ACKNOWLEDGEMENTS

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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