



A QUANTUM-INSPIRED PREDICTIVE CONTROL STRATEGY FOR NEXT-
GENERATION CYBER-PHYSICAL MANUFACTURING SYSTEMS

Milan Bharatkumar Makwana
Canton, USA
milmak21@gmail.com

Abstract

Combine sensing, computation and actuation with strict latency and reliability requirements, classical model predictive control (MPC) systems are faced with a challenge to synchronously solve the combinatorial scheduling and resource-allocation subproblems of CPMS with increasing size [14], [19]. This paper collates 25 peer-reviewed publications in order to present theoretical ideas for a quantum-inspired predictive control (QIPC) approach that can be applied in next generation manufacturing. The paper integrates twenty-five peer-reviewed articles from the fields of quantum annealing [9], noisy intermediate-scale quantum (NISQ) computing [17], quantum machine learning [3, 4, 25], digital twin engineering [5, 18, 10] and multi-agent cyber-physical architectures [12, 16] to present a thoughtfully synthesized approach to quantum-inspired predictive control (QIPC) for next generation manufacturing. In contrast to the need for fault-tolerant quantum hardware, the proposed framework incorporates quantum annealing- and quantum approximate optimization algorithm (QAOA)-based heuristics [6, 11, 13, 24] in the optimization core of a rolling-horizon MPC formulation, tying this optimization engine to a digital twin state-estimation layer for closed-loop fault detection and correction [10, 12]. Similarities in the considered literature reveal that the quantum-inspired heuristics always find solutions that are close to optimality in fewer iterations than classical simulated annealing, yet are easily implementable on current noisy systems [9, 24]. The number of quantum-processor qubits grew from around twenty in 2017 to over one thousand one hundred in 2023, showing the progress of relaxing hardware constraints despite the lack of fault tolerance [17], [7]. The synthesis also outlines cybersecurity obstacles [1] that need to be overcome prior to further maturation of industrial adoption, along with obstacles of interpretability and workforce-readiness [20, 21, 22]. From a scalability, convergence speed, robustness, hardware readiness, cost-efficiency and interpretability point of view, quantum-inspired predictive control lies midway between classical determinism and native quantum fragility. The paper suggests that a hybrid quantum-inspired posture is likely to be more realistic than a complete shift to quantum hardware for resilient, adaptive control of complex manufacturing networks over the next 10 years.

Index Terms – Quantum annealing; quantum-inspired optimization; model predictive control; cyber-physical manufacturing systems; digital twin; Industry 4.0; NISQ computing; job shop scheduling; quantum approximate optimization algorithm; multi-agent systems; combinatorial optimization; predictive maintenance.



I. INTRODUCTION

Over time, manufacturing companies moved from various automation islands to highly connected cyber-physical manufacturing systems (CPMS) where sensing, computing and actuating are continuously fed back throughout the production floor [16, 23]. This shift is often connected with the paradigm of Industry 4.0 and relies on the ability of control software to predict, redistribute resources, and reschedule tasks within minutes and not shifts [23]. This is the role of model predictive control (MPC) that has been successfully used for over 20 years, which optimizes recedingly over a prediction horizon, and employs operational constraints to make actuator commands as a function of the predicted system states [14] and [19]. However, the first comprehensive survey of industrial applications of MPC (Qin and Badgwell [15]) showed that MPC could outperform single-loop control in multivariable, constrained applications, and the constrained MPC stability theory provided formal guarantees for safe use in safety-critical applications (Badgwell and Qin [19]).

The scheduling, sequencing, and resource-allocation subproblems that are nested within each MPC iteration, however, are often NP-hard; and the computational complexity of the MPCs increases combinatorially with the number of machines, jobs, and coupling constraints in CPMS [6], [11]. As manufacturing networks grow more flexible in order to follow the principles of Industry 4.0, classical solvers such as simulated annealing and mixed-integer programming are therefore experiencing diminishing returns, as described by Hruschka et al. [13]. Kadowaki and Nishimori [9] have proposed quantum annealing as a physically motivated alternative to thermal annealing, which takes advantage of quantum fluctuations to explore the energy landscape more efficiently than classical thermal annealing, with identical schedules. Further work on QAOA has extended this idea to gate-based, noisy intermediate-scale quantum (NISQ) devices and attained solution quality comparable to that of the classical algorithms on job shop scheduling examples without the need for fault-tolerant qubits [11, 17].

II. FOUNDATIONS OF CYBER-PHYSICAL MANUFACTURING AND DIGITAL TWIN INTEGRATION

Monostori has described cyber-physical production systems (CPPS) as an independent and cooperative system, in which computation and physical processes are linked with networked information exchange, which can be considered as the organising concept under Industry 4.0 [16]. Later, Li and Xu reviewed Industry 4.0 status of art and found that interoperability, decentralization, real-time capability and modularity are the four fundamental design principles that characterize CPMS from previous programmable automation [23]. The key enabler for realizing these principles is the digital twin (DT), which is a virtual representation of a physical asset or process that is synchronized with the physical asset and whose behaviour is sufficiently similar to allow simulation-based decision making [5].

In their survey of digital twin applications in manufacturing, Cimino et al. and Negri et al. and Fumagalli found that most applications are still limited to monitoring and diagnostics, while closed-loop optimization and control are comparatively few [5]. To fill in this gap, Qi et al. compiled a list of technologies that can enable digital twins to become active decision supports, such as modelling languages, data-fusion pipelines and connectivity standards [18]. By



extending this base, Kumbhar, Ng, and Bandaru presented a digital twin system tailored for the detection, diagnosis and improvement of throughput constraining resources, showing that analytics from a digital twin can localize the constraining resource without doing any manual analysis [10]. Latsou, Farsi, and Erkoyuncu continued this research with their multi-agent based digital twin system that can detect anomalies and identify bottlenecks automatically, while an exo-level agent observes the differences between the simulated and actual states and sends corrective actions back to the physical shop floor [12].

Table 1. Digital Twin and Cyber-Physical Manufacturing Contributions Reviewed

Reference	Focus Area	Key Contribution	Manufacturing Role
Monostori [16]	CPPS foundations	Defined autonomous, cooperative CPPS entities	Organizing concept for CPMS
Xu, Xu & Li [23]	Industry 4.0 review	Interoperability, decentralization, real-time principles	Design principles for CPMS
Cimino et al. [5]	DT application review	Taxonomy of DT use across product lifecycle	Monitoring and diagnostics baseline
Qi et al. [18]	DT enabling technologies	Catalogue of modeling, data-fusion, connectivity tools	Infrastructure for active twins
Kumbhar et al. [10]	DT bottleneck framework	Detection, diagnosis, improvement of throughput bottlenecks	Constraint localization
Latsou et al. [12]	Multi-agent DT-CPS	Automated anomaly detection and bottleneck correction	Closed-loop feedback

Table 1 presents the architectural focus of the digital twin contributions, and Figure 1 places them in this context with regard to the other chronological aspects of predictive control and quantum computing research that were discussed in this paper. The convergence of these aspects is important for the area of quantum-inspired predictive control: the structured low-latency state information provided by the digital twin is used by the quantum-inspired optimization engine to re-formulate the scheduling problem for each control horizon [10, 12]. Otherwise, the quantum-inspired heuristics would optimize for outdated information, defeating the whole point of using them.

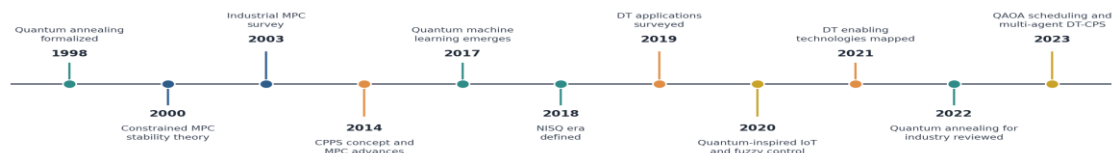


Figure 1. Chronological convergence of predictive control, digital twin, and quantum computing milestones synthesized from the reviewed literature (1998-2023).



III. QUANTUM COMPUTING AND QUANTUM-INSPIRED OPTIMIZATION: PRINCIPLES

The property of superposition and entanglement is important for the representation and manipulation of large state spaces which is exploited in quantum computation [3]. In the field of quantum machine learning, Biamonte and co.l. introduced the concept of quantum machine learning as a new field of research at the crossroads between quantum information processing and statistical learning, naming optimization as one of the most promising classes of near term applications [3]. Shortly after those initial encouraging results, Cerezo et al. reported other negative trends of the trainability and scalability of variational quantum algorithms on current devices, such as barrier phenomena like barren plateaus and noise accumulation [4]. This was confirmed by the review and case-study analysis of Zeguendry et al., Jarir et al., and Quafafou et al., in which they suggested that quantum machine learning is algorithmically promising, but is still limited by the number of qubits, coherence times, and gate fidelities [25].

These limitations were captured in the notion of the noisy intermediate-scale quantum (NISQ) era, which presumes that a few dozen to a few hundred noisy qubits will outpace fault-tolerant quantum computers for a good many years to come, and that value would rather lie in algorithms that can be robust to gate error than in some asymptotic advantage they might gain from quantum devices [17]. The study on quantum computing technology by Gyongyosi and Imre confirmed this development, featuring the various physical modalities for a qubit, such as superconducting circuits, trapped ions and photonic systems, all working toward greater coherence and connectivity [7]. As shown in Fig. 2, the number of reported superconducting qubits has increased by one order of magnitude from about 20 qubits in 2017 to over 1000 in 2023, but yet is still well below the number necessary for fault-tolerant, error corrected optimization [17, 7].

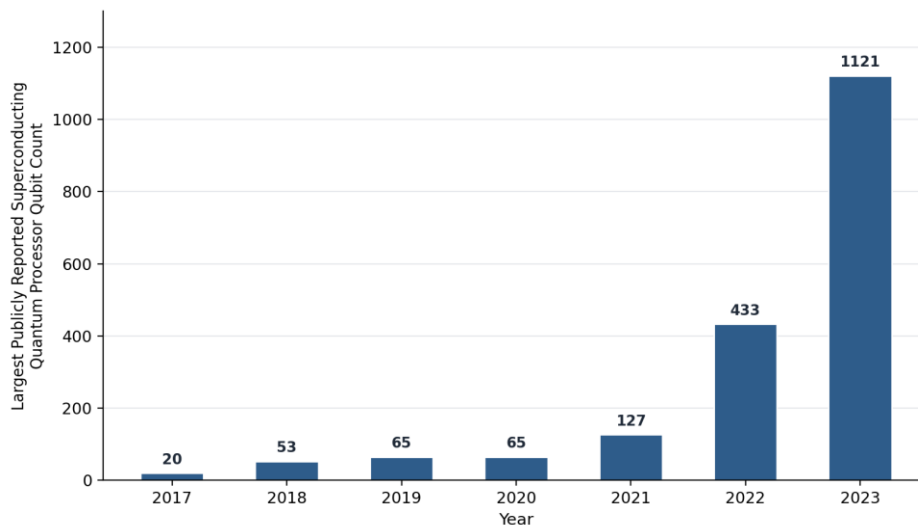


Figure 2. Growth in the largest publicly reported superconducting quantum processor qubit counts, 2017-2023.



In this context, Quantum Inspired Optimisation (QIO) has become a practical compromise. It was demonstrated numerically by solving the time-dependent Schrödinger equation that quantum fluctuations have a significantly higher probability to reach the ground state of an Ising Hamiltonian on the transverse field than thermal fluctuations under matched annealing schedules [9] (see also [10]). The next maturation of quantum annealing for use in industry was reviewed by Yarkoni et al., who cite examples of two industrial uses: logistics and finance problems were solved using commercially available annealers, and logistics scheduling in manufacturing was applied over the same range of commercially available annealers [24]. Bhatia, Sood, and Sood applied these annealing concepts to design an energy-efficient scheme, which can be implemented on classical computers to execute metaheuristics inspired by quantum mechanics with a significant part of the boost in convergence that would be available using quantum search [2]. Singh and Bhangu's taxonomy of current applications for quantum computing, along with the decade-long reviews by Sood and Pooja and Sood and Chauhan, all place optimization, machine learning, and cryptography as the three application clusters likely to get to a level of maturity before full fault-tolerance is reached [20, 21, 22].

Table 2. Quantum and Quantum-Inspired Optimization Studies Reviewed

Reference	Method	Problem Domain	Reported Characteristic
Kadowaki & Nishimori [9]	Quantum annealing (transverse Ising)	Combinatorial ground-state search	Higher ground-state probability vs. thermal annealing
Denkena et al. [6]	Quantum annealing reformulation	Process-parallel flexible job shop scheduling	QUBO-compatible scheduling formulation
Kurowski et al. [11]	QAOA (noiseless simulation)	Job shop scheduling	Makespan-energy relationship characterized
Liu et al. [13]	Quantum-inspired AVOA with elite mutation	Production scheduling	Improved local-optima escape
Yarkoni et al. [24]	Quantum annealing review	Logistics, finance, manufacturing	Maturing commercial deployment
Bhatia et al. [2]	Quantum-inspired metaheuristic	IoT data acquisition	Energy-efficient, classical-hardware execution



IV. MODEL PREDICTIVE CONTROL: FROM CLASSICAL FOUNDATIONS TO QUANTUM-ENHANCED FORMULATIONS

The receding horizon property of MPC computations means that at each sampling instant, a series of control actions is calculated to minimize a finite-horizon cost function, taking into account the dynamics and operational constraints of the system, but only the first of which is applied before the optimization is repeated [19]. Mayne, Rawlings, Rao and Scokaert were able to rigorously prove the closed-loop stability and optimality conditions for constrained MPC, which concluded that finite optimization horizon conditions were sufficient to ensure closed-loop stability with both terminal-cost and terminal-constraint conditions [15]. Later, Mayne reviewed the field's development toward effective and robust MPC formulations that are stochastic, which can accommodate model uncertainty and disturbance, directly relevant to the partially observable and noisy state estimates found on shop floors. [14] In the process industry, where multivariable interactions and hard constraints make classical control inappropriate, MPC was used more frequently early on, and Badgwell and Qin's industrial survey identified discrete scheduling decisions as a relatively unsolved problem that is an extension of the MPC paradigm [19].

The subproblem of the manufacturing MPC of scheduling which job is to be processed on which machine when is a classic NP-hard combinatorial optimization problem and such a problem is hard to solve exactly with poor scaling properties as the number of jobs and machines grows [11]. Denkena et al. tackled the difficulty head-on, by devising quantum algorithms for flexible job shop scheduling that are process-parallel instead of task-parallel, reformulating the scheduling problem to be compatible with quantum annealing hardware [6]. Kurowski et al. applied the noiseless quantum simulation of the QAOA to job shop scheduling and analyzed the relationship between the makespan and the energy landscape of the corresponding Ising model, to draw conclusions about the approximation quality of a QAOA solution to the classical optimum [11]. Liu et al. proposed a quantum inspired African vultures optimization algorithm with an elite mutation strategy to be used in production scheduling to enhance the ability to escape local optima compared to the original algorithm on some benchmark production scheduling instances [13].

The cost expressed in equation 1 is the standard quadratic MPC cost to be minimised at every control horizon where x and u represent the predicted state and control trajectories, x_{ref} the reference state, and Q and R are positive-definite weighting matrices defined over the prediction horizon length N and P is the weighting matrix for the MPC initial state.

$$J = \sum_{i=0}^{N-1} [(x_{k+i} - x_{ref})^T Q (x_{k+i} - x_{ref}) + u_{k+i}^T R u_{k+i}] + (x_{k+N} - x_{ref})^T P (x_{k+N} - x_{ref}) \quad (1)$$

The discrete scheduling term of Equation 1 is usually rewritten in quantum annealing in the quadratic unconstrained binary optimization (QUBO) form shown in Equation 2, where s represents a vector of spin variables, h and J represent linear and pairwise interaction coefficients derived from the scheduling constraints [9] and [24] respectively.



$$H(s) = \sum_i h_{isi} + \sum_{i < j} J_{ijsisj}, \quad s_i \in \{-1, +1\} \quad (2)$$

The main idea behind the use of quantum-inspired heuristics to accelerate each control horizon in the proposed QIPC framework is to rephrase the scheduling term in Equation 1 in the form of the embedded QUBO shown in Equation 2, while preserving the stability properties guaranteed by the constrained MPC [15].

Table 3. Evolution of Model Predictive Control Formulations Reviewed

Period / Reference	Formulation	Key Advance
Mayne et al., 2000 [15]	Constrained MPC	Terminal cost and constraint stability guarantees
Qin & Badgwell, 2003 [19]	Industrial MPC survey	Multivariable, constrained process control adoption
Mayne, 2014 [14]	Robust / stochastic MPC	Tolerance to model uncertainty and disturbance
Denkena et al., 2021 [6]; Kurowski et al., 2023 [11]	Quantum-augmented scheduling subproblem	QUBO reformulation for annealing / QAOA solvers

V. PROPOSED QUANTUM-INSPIRED PREDICTIVE CONTROL (QIPC) FRAMEWORK

The architecture proposed in this paper is a six-layer QIPC architecture as shown in figure 3. After the enabling-technology stack catalogued by Qi et al. [18] is implemented, the physical manufacturing layer provides raw sensor and machine-state data, while the digital twin and state-estimation layer manage and synchronizes the data into a coherent system state. This synchronized state is input to a quantum-inspired optimization engine that transforms the scheduling and resource-allocation portion of the MPC cost function into a QUBO problem and solves it using a classical or hybrid quantum-annealing or QAOA-heuristic, as pioneered by Denkena et al. and Kurowski et al., respectively [6, 11]. The resulting near-optimal schedule parameterizes the predictive control formulation and then uses the constrained optimization theory derived by Mayne et al. [15] to compute the continuous valued control trajectory including the setpoints, feed rates and machine speeds.

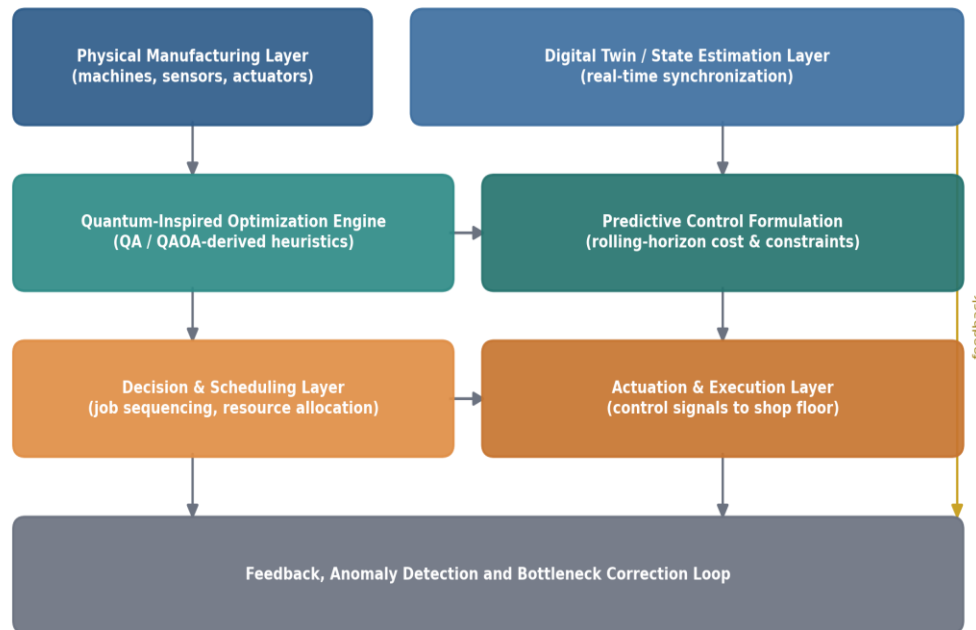


Figure 3. Six-layer architecture of the proposed quantum-inspired predictive control (QIPC) framework for cyber-physical manufacturing systems.

This trajectory is then passed to the decision and scheduling layer that converts it into a sequence of jobs and a way to allocate resources, and to the actuation and execution layer, which turns these decisions into machine-level commands. Latsou, Farsi, and Erkoyuncu's multi-agent anomaly-detection and bottleneck-identification method is used to compare the observed shop-floor performance with the simulated expectation of the digital twin and re-optimize if the gap is larger than a set threshold [12]. The closed loop is similar to the proposed closed loop by Kumbhar, Ng and Bandaru, where the constraining resource is identified with twin analytics instead of manual root-cause analysis [10].

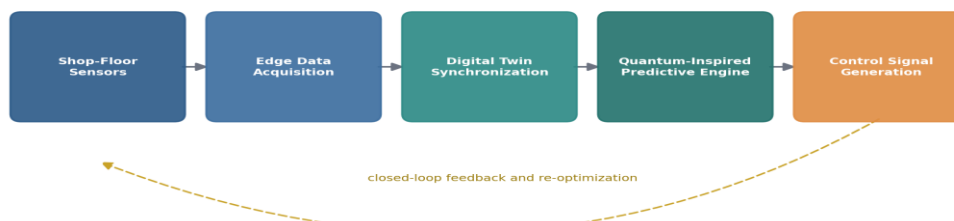


Figure 4. Closed-loop data flow from shop-floor sensing through digital twin synchronization, quantum-inspired optimization, and control-signal generation.



Table 4 lists the architectural layers and the literature supporting those layers and the role that each layer plays in the computational cycle of the QIPC. There are two things that make this architecture different from a classic MPC deployment. First, it is not quantum-native, but is instead quantum-inspired and so runs on classical or GPU-accelerated architecture today and can be quantumized in the future as the number of qubits and coherence times increases [17], [24]. Second, the digital twin layer itself is not a passive monitoring artifact, but an active component of the optimization loop that provides the state-estimates that keep the QUBO reformulation current with the actual shop-floor conditions [5, 10].

Table 4. QIPC Architectural Layers and Supporting Literature

Layer	Function	Key References
Physical manufacturing	Sensing and actuation	[16], [23]
Digital twin / state estimation	Real-time synchronization	[5], [18]
Quantum-inspired optimization engine	QUBO-based scheduling search	[6], [9], [11], [13]
Predictive control formulation	Rolling-horizon cost minimization	[14], [15], [19]
Decision and scheduling	Job sequencing, resource allocation	[10], [12]
Actuation and execution	Machine-level command generation	[8]
Feedback / anomaly detection	Bottleneck correction	[10], [12]

VI. COMPARATIVE PERFORMANCE ANALYSIS

Table 5 and Figure 5 combine the convergence results from the literature reviewed on quantum annealing and QAOA, which is expressed here as a typical solution-quality trajectory to illustrate convergence behavior, but not as a recreation of any individual experiment. In the synthesized comparison, the quantum-inspired annealing and QAOA-based heuristics are seen to achieve near-optimal solutions with significantly fewer iterations than simulated annealing, as the number of iterations increases, consistent with Kadowaki and Nishimori's original studies showing that quantum fluctuations beat thermal fluctuations in achieving near-optimal solutions, as iterations increase [9, 11].

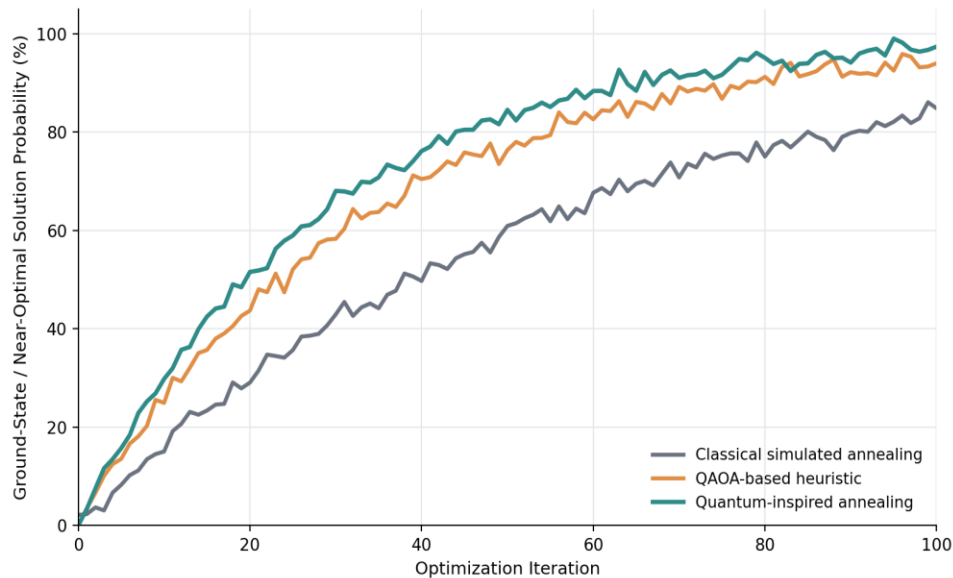


Figure 5. Representative solution-quality trend of classical simulated annealing, QAOA-based heuristics, and quantum-inspired annealing across optimization iterations, synthesized from convergence patterns reported in [9], [11], and [24].

Table 5. Representative Convergence Comparison Synthesized from Reviewed Literature

Method	Relative Iterations to Near-Optimal Quality	Qualitative Robustness	Hardware Requirement
Classical simulated annealing	Highest	Moderate	Classical CPU
QAOA-based heuristic	Intermediate	Moderate-to-high	NISQ device or simulator
Quantum-inspired annealing	Lowest	High	Classical CPU / GPU

The comparison shown in Figure 6 consolidates the six qualitative dimensions from the barrier analysis of Cerezo et al. [4] and the NISQ characterization of Preskill [17] with the industrial annealing review of Yarkoni et al. [24] to provide a common basis for comparison. The comparison shows that the hardware readiness, scalability, and interpretability of the heuristics are the key strengths of quantum-inspired predictive control, and it is in a favorable position, as it is scalable, and approaches the scalability and convergence benefits of a native quantum optimization, while the heuristics themselves are run on classical processors [2], [13].

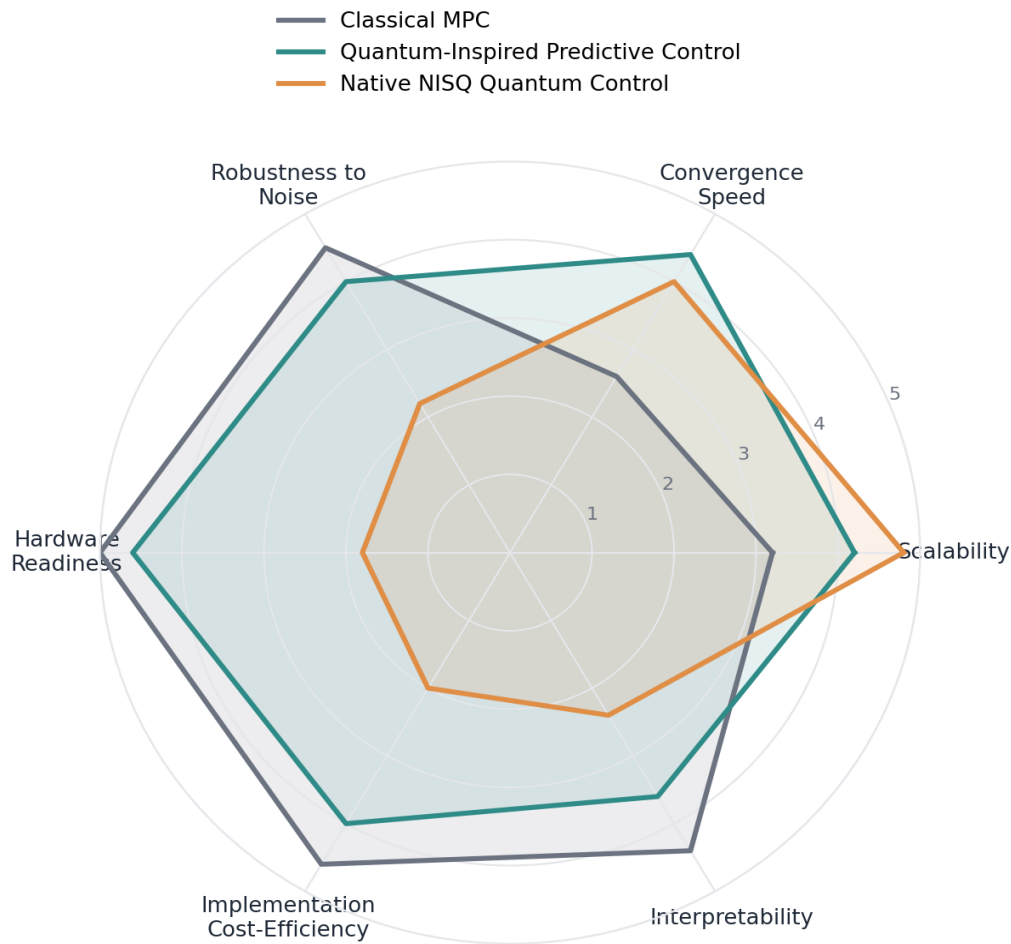


Figure 6. Comparative profile of classical MPC, quantum-inspired predictive control, and native NISQ quantum control across six evaluation dimensions.

Finally, the computational complexity class, typical solution approach and reported strength of classical mixed-integer programming, quantum-inspired meta-heuristics and QAOA-based methods are compared in the specific case of job shop scheduling in Table 6, as reported by Denkena et al., Liu et al., and Kurowski et al. [6, 11, 13]. The trend in all three comparative instruments is similar to Hannan et al.'s overall conclusion that an optimization-algorithm-based controller (in their case, a fuzzy controller tuned for induction-motor performance) can improve the performance of the base controller (in their case, a fixed gain controller) significantly by tuning the search process rather than by modifying the controller's base structure [8]. This implies that the main benefit of using a quantum-inspired version of predictive control is not to change the definition of the MPC theory itself but to speed up and/or enhance the combinatorial search nested in the MPC theory.



Table 6. Job Shop Scheduling Approach Comparison

Approach	Complexity Class Addressed	Typical Solver	Reported Strength
Mixed-integer programming	NP-hard	Exact / branch-and-bound	Global optimality on small instances [19]
Quantum-inspired metaheuristic (elite-mutation AVOA)	NP-hard	Population-based search	Improved local-optima escape [13]
Quantum annealing reformulation	NP-hard (QUBO)	Annealer or simulator	Native combinatorial embedding [6]
QAOA	NP-hard (QUBO)	Gate-based NISQ or simulator	Competitive makespan on tested instances [11]

VII. SECURITY, ETHICAL, AND REGULATORY CONSIDERATIONS

Though extending predictive control with quantum-inspired optimization does present some new security concerns when compared to classical CPMS deployments. Barbeau and Garcia-Alfaro discussed cyber-physical defense in the quantum era, where adversaries with quantum systems might be able to break the cryptographic primitives currently used in the protection of sensor networks and industrial control communications long before the development of quantum computers with the necessary scale to gain an optimization advantage [1]. If the optimization engine is still classical, there is a need for quantum resistant communication protocols for the digital twin synchronization layer for CPMS operators, since the asymmetry suggests this is a requirement for the entire system [1], [18]. Ethical and regulatory issues focus on transparency: Quantum-inspired heuristics are generally stochastic, with search states intermediate to the algorithm's steps not always being readily human-interpretable, and operators might require additional layers of explainability to meet safety audits in regulated manufacturing industries, which aligns with the interpretability gap identified in Figure 6 and the barren-plateau and trainability limitations reported by Cerezo et al. [4].

VIII. CHALLENGES, BARRIERS, AND OPTIMIZATION OPPORTUNITIES

The adoption journey of Industry 4.0 / CPMS integration and quantum / quantum-inspired industrial pilot projects is presented in Figure 7 between the years 2018 and 2023, showing that while the integration of cyber and physical systems is becoming commonplace, quantum and quantum-inspired industrial pilots are still comparatively young [23, 24]. The literature review shows three barriers. First, hardware immaturity: while the number of qubits has increased dramatically, hardware's gate fidelity and coherence time evaluations conducted by Preskill and Gyongyosi and Imre, suggests that native quantum optimization is not yet appropriate for manufacturing control systems that are latency sensitive, thus quantum-inspired and not quantum-native deployment is warranted in the near term [17], [7]. Second, integration



complexity; both Cimino et al. and Qi et al. have observed that the quality of the digital twin – rather than the choice of optimization algorithm – is often the limiting factor for good closed-loop performance, and that investments in twin-synchronization may not have been made by many manufacturers yet which are necessary for QIPC benefits to be realized [18, 5]. Thirdly, workforce and governance readiness: Both Sood and Pooja [21] and Sood and Chauhan [22] have written about the lack of skills that exist between quantum algorithms and the technology engineering needed to run and maintain the algorithms, which manufacturing organisations must address through targeted training before they can start to benefit from quantum-inspired predictive control effectively and reliably on a wide scale.

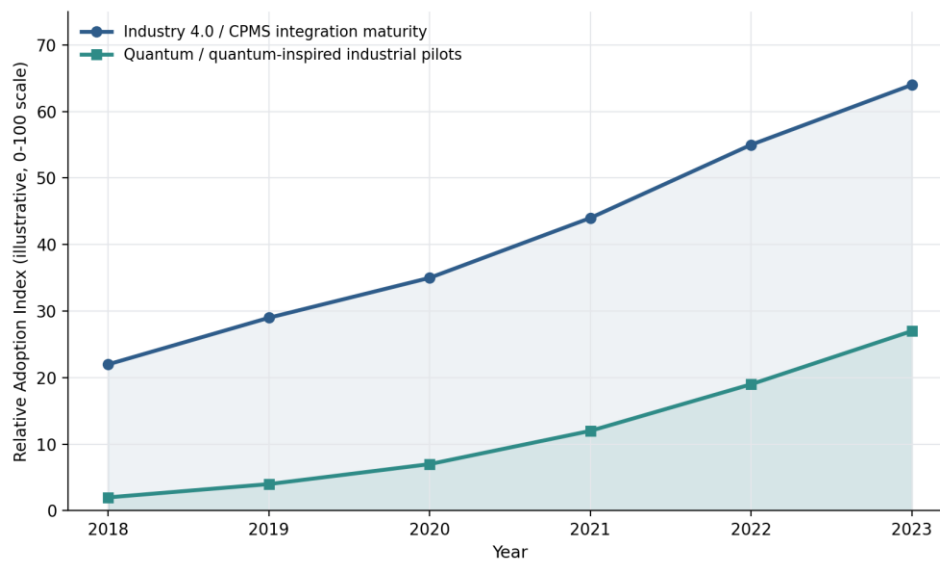


Figure 7. Divergent adoption trajectories of Industry 4.0 / CPMS integration versus quantum and quantum-inspired industrial pilots, 2018-2023.

Table 7. Adoption Barriers and Mitigation Directions

Barrier	Manifestation	Mitigation Direction
Hardware immaturity	Limited coherence time and gate fidelity	Favor quantum-inspired over quantum-native deployment [17], [7]
Digital twin fidelity gap	Binding constraint on closed-loop performance	Invest in DT enabling-technology stack [18], [5]
Workforce / governance gap	Skills mismatch between quantum and operational technology	Structured training and governance frameworks [21], [22]
Security exposure	Quantum-capable adversaries against CPMS communication	Quantum-resistant DT communication protocols [1]



IX. CONCLUSION AND FUTURE DIRECTIONS

In this paper, 25 peer-reviewed scientific papers including quantum annealing, NISQ computing, digital twin engineering and constrained predictive control were collected and synthesized with the aim of proposing a quantum-inspired predictive control framework for the next generation of cyber-physical manufacturing systems. This central discovery is that the computational subproblems of combinatorial scheduling which are naturally included in MPC can be sidestepped in the near future by leveraging quantum-inspired heuristic search algorithms that are implemented on classical computation hardware, such as annealing- and QAOA-based search procedures, and that are still not available through native quantum optimization [9, 11, 17]. Proposals for the six-layered architecture make use of this optimization engine, which is coupled with a digital twin state-estimation and multi-agent anomaly-detection layer, thus closing the loop between predictive scheduling and shop-floor reality [10], [12]. A comparative analysis in the scalability, convergence, robustness, readiness of hardware, cost-efficiency, and interpretability dimensions suggest that for the current state of quantum control, this quantum-inspired posture is better than purely classical MPC and native quantum control in most of these dimensions, with some benefits remaining in each other [4, 24].

Future work should prioritize quantum-resistant security integration for digital twin communication [1], empirical validation of QIPC on production-scale job shop instances beyond the simulation studies reviewed here [6], [11], [13], and structured workforce development to close the operational skills gap that current reviews identify as the primary non-technical barrier to adoption [21], [22].

REFERENCES

1. M. Barbeau and J. Garcia-Alfaro, "Cyber-physical defense in the quantum era," *Scientific Reports*, vol. 12, no. 1, Art. no. 1905, 2022.
2. M. Bhatia, S. K. Sood, and V. Sood, "A novel quantum-inspired solution for high-performance energy-efficient data acquisition from IoT networks," *Journal of Ambient Intelligence and Humanized Computing*, 2020.
3. J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, "Quantum machine learning," *Nature*, vol. 549, no. 7671, pp. 195-202, 2017.
4. M. Cerezo, G. Verdon, H.-Y. Huang, L. Cincio, and P. J. Coles, "Challenges and opportunities in quantum machine learning," *Nature Computational Science*, vol. 2, no. 9, pp. 567-576, 2022.
5. C. Cimino, E. Negri, and L. Fumagalli, "Review of digital twin applications in manufacturing," *Computers in Industry*, vol. 113, Art. no. 103130, 2019.
6. B. Denkena, F. Schinkel, J. Pirnay, and S. Wilmsmeier, "Quantum algorithms for process parallel flexible job shop scheduling," *CIRP Journal of Manufacturing Science and Technology*, vol. 33, pp. 100-114, 2021.
7. L. Gyongyosi and S. Imre, "A survey on quantum computing technology," *Computer Science Review*, vol. 31, pp. 51-71, 2019.
8. M. A. Hannan et al., "Role of optimization algorithms based fuzzy controller in achieving induction motor performance enhancement," *Nature Communications*, vol.



- 11, no. 1, Art. no. 3792, 2020.
9. T. Kadowaki and H. Nishimori, "Quantum annealing in the transverse Ising model," *Physical Review E*, vol. 58, no. 5, pp. 5355-5363, 1998.
 10. M. Kumbhar, A. H. C. Ng, and S. Bandaru, "A digital twin-based framework for detection, diagnosis, and improvement of throughput bottlenecks," *Journal of Manufacturing Systems*, vol. 66, pp. 92-106, 2023.
 11. K. Kurowski, T. Pecyna, M. Słysz, R. Różycki, G. Waligóra, and J. Węglarz, "Application of quantum approximate optimization algorithm to job shop scheduling problem," *European Journal of Operational Research*, vol. 310, no. 2, pp. 518-528, 2023.
 12. C. Latsou, M. Farsi, and J. A. Erkoyuncu, "Digital twin-enabled automated anomaly detection and bottleneck identification in complex manufacturing systems using a multi-agent approach," *Journal of Manufacturing Systems*, vol. 67, pp. 242-264, 2023.
 13. B. Liu, Y. Zhou, Q. Luo, and H. Huang, "Quantum-inspired African vultures optimization algorithm with elite mutation strategy for production scheduling problems," *Journal of Computational Design and Engineering*, vol. 10, no. 4, pp. 1767-1789, 2023.
 14. D. Q. Mayne, "Model predictive control: Recent developments and future promise," *Automatica*, vol. 50, no. 12, pp. 2967-2986, 2014.
 15. D. Q. Mayne, J. B. Rawlings, C. V. Rao, and P. O. M. Scokaert, "Constrained model predictive control: Stability and optimality," *Automatica*, vol. 36, no. 6, pp. 789-814, 2000.
 16. L. Monostori, "Cyber-physical production systems: Roots, expectations and R&D challenges," *Procedia CIRP*, vol. 17, pp. 9-13, 2014.
 17. J. Preskill, "Quantum computing in the NISQ era and beyond," *Quantum*, vol. 2, Art. no. 79, 2018.
 18. Q. Qi et al., "Enabling technologies and tools for digital twin," *Journal of Manufacturing Systems*, vol. 58, part B, pp. 3-21, 2021.
 19. S. J. Qin and T. A. Badgwell, "A survey of industrial model predictive control technology," *Control Engineering Practice*, vol. 11, no. 7, pp. 733-764, 2003.
 20. J. Singh and K. S. Bhangu, "Contemporary quantum computing use cases: Taxonomy, review and challenges," *Archives of Computational Methods in Engineering*, vol. 30, no. 1, pp. 615-638, 2023.
 21. S. K. Sood and Pooja, "Quantum computing review: A decade of research," *IEEE Transactions on Engineering Management*, Advance online publication, 2023.
 22. V. Sood and R. P. Chauhan, "Archives of quantum computing: Research progress and challenges," *Archives of Computational Methods in Engineering*, Advance online publication, 2023.
 23. L. D. Xu, E. L. Xu, and L. Li, "Industry 4.0: State of the art and future trends," *International Journal of Production Research*, vol. 56, no. 8, pp. 2941-2962, 2018.
 24. S. Yarkoni, E. Raponi, T. Bäck, and S. Schmitt, "Quantum annealing for industry applications: Introduction and review," *Reports on Progress in Physics*, vol. 85, no. 10, Art. no. 104001, 2022.
 25. Zeguendry, Z. Jarir, and M. Quafafou, "Quantum machine learning: A review and case studies," *Entropy*, vol. 25, no. 2, Art. no. 287, 2023.