AI–Quantum Hybrid Optimisation for Product Engineering in the NISQ Era

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Short Abstract: Modern product engineering faces optimisation problems of increasing complexity, driven by multi-physics coupling, combinatorial design spaces, and conflicting objectives. Classical optimisation and artificial intelligence approaches, while effective, encounter fundamental computational limits. This paper explores hybrid Artificial Intelligence–Quantum Computing optimisation frameworks as emerging tools for engineering design. We review foundational concepts, recent technological solutions, and applied case studies, highlighting challenges and innovations in quantum-assisted optimisation for product engineering.

Key words: Product engineering, optimisation, artificial intelligence, quantum computing, hybrid algorithms

1- Introduction and Problem Statement

Product engineering is intrinsically linked to optimisation. Engineers must continuously balance competing objectives such as performance, cost, manufacturability, sustainability, and reliability throughout the product lifecycle. Classical design methodologies formalise this process as an iterative loop of synthesis, analysis, and evaluation, where optimisation plays a central role (PAHL G., BEITZ W., Engineering Design, Springer Verlag, London, 1988).

However, the growing integration of mechanical systems, electronics, software, and complex supply chains has led to design spaces of unprecedented size and complexity. Many modern engineering problems are combinatorial, multi-objective, and non-linear, rendering exhaustive search infeasible. Even advanced numerical optimisation techniques struggle to scale efficiently.

Artificial Intelligence (AI) has become a key enabler for addressing these challenges, notably through machine learning and data-driven optimisation. Yet, AI-based methods remain bounded by classical computational resources, particularly for discrete optimisation problems. This limitation motivates the exploration of alternative computational paradigms, including quantum computing.

2- Scientific Foundations of AI-Based Optimisation

2.1- Machine Learning and Surrogate Modelling

AI techniques are widely used in product engineering to accelerate optimisation processes. Surrogate models approximate expensive simulations, such as finite element or computational fluid dynamics analyses, using learned relationships derived from data. These models significantly reduce computational cost and enable broader exploration of design spaces.

2.2- Multi-objective Optimisation and Decision Support

Engineering optimisation often involves conflicting objectives. Evolutionary algorithms, Bayesian optimisation, and neural-network-based approaches enable the identification of Pareto-optimal solutions, supporting informed engineering decisions rather than purely numerical optima.

2.3- Reinforcement Learning for Sequential Engineering Problems

Reinforcement learning is particularly suited to sequential decision-making problems, such as process planning, lifecycle optimisation, and logistics. The system learns optimal strategies through interaction with a simulated environment, enabling adaptive optimisation under uncertainty.

Despite these successes, AI remains constrained by classical computational limits when addressing large-scale combinatorial problems.

3- Quantum Algorithmics for Engineering Optimisation

3.1- Quantum Computing Principles Relevant to Optimisation

Quantum computing relies on quantum-mechanical principles such as superposition and entanglement. Quantum bits can represent multiple states simultaneously, enabling new ways of exploring large solution spaces.

3.2- Quantum Optimisation Algorithms

One of the most prominent quantum optimisation algorithms is the Quantum Approximate Optimization Algorithm (QAOA), a hybrid quantum–classical method designed for combinatorial optimisation (FARHI E. et al., “A Quantum Approximate Optimization Algorithm”, arXiv, 2014). Another important approach is quantum annealing, which exploits quantum tunnelling to escape local minima and is well suited to problems formulated as Quadratic Unconstrained Binary Optimization (QUBO).

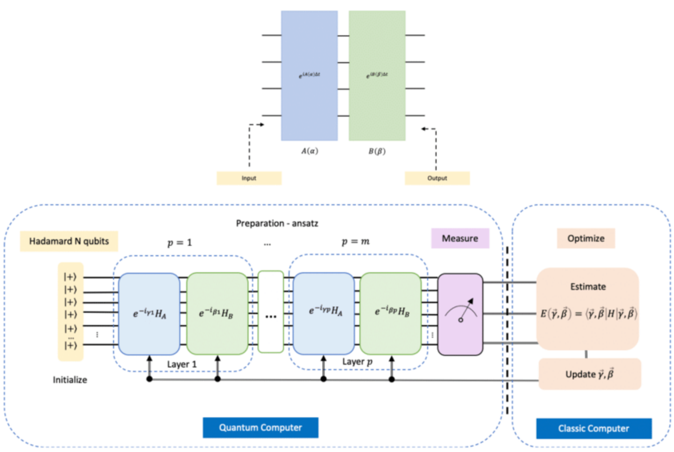

Figure 1: Schematic representation of the Quantum Approximate Optimization Algorithm (QAOA)

3.3- Limitations of Current Quantum Hardware

Current quantum devices operate in the Noisy Intermediate-Scale Quantum (NISQ) era. Noise, limited qubit counts, and decoherence restrict purely quantum solutions, making hybrid approaches necessary.

4- Hybrid AI–Quantum Optimisation Solutions

Hybrid AI–quantum approaches combine classical AI with quantum optimisation as a specialised accelerator. AI assists in problem formulation, parameter tuning, and noise mitigation, while quantum algorithms address discrete optimisation subproblems.
Recent studies demonstrate applications in: topology optimisation of structures using quantum annealing, composite material stacking sequence optimisation, factory layout planning and scheduling, and disassembly sequence optimisation for sustainable manufacturing.

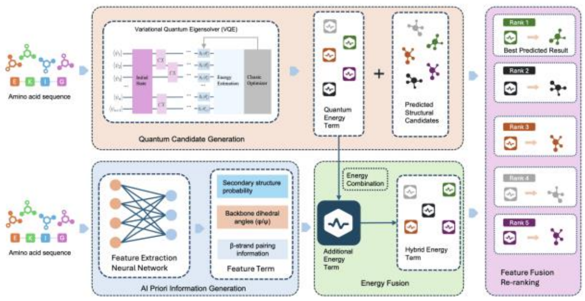

Figure 2: Architecture of a Dual-Branch Hybrid Quantum-AI Framework.

5- Challenges, Innovations, and Specificities

5.1- Challenges

Quantum engineering faces several challenges, including the need to encode traditional engineering problems into formulations compatible with quantum systems. There's also the issue of hardware noise, which affects the accuracy and reliability of computations. Additionally, integrating these techniques into existing engineering workflows is complex and requires careful adaptation.

5.2- Innovations

To tackle these challenges, several innovations have emerged. AI-guided quantum parameter optimization enhances the efficiency of quantum algorithms. Quantum-enhanced generative models are being used in materials engineering to discover new materials with desired properties. Furthermore, automated problem formulation pipelines are being developed to simplify the translation of engineering issues into formats suitable for quantum solutions.

5.3- Specificities of the Technology

AI–quantum optimisation does not replace engineers; it augments their ability to explore complex design spaces and manage uncertainty.

6- Definition of the Core Concept and Tools

AI–Quantum Hybrid Optimisation is defined as the coordinated use of artificial intelligence and quantum algorithms to solve engineering optimisation problems beyond classical computational feasibility.
Key tools in this domain include machine learning and surrogate modelling frameworks, reinforcement learning environments, QAOA (Quantum Approximate Optimization Algorithm) and quantum annealing solvers, as well as classical-quantum optimization loops.

7- Conclusion and Perspectives

AI and quantum algorithmics together represent a methodological evolution in product engineering. While quantum advantage is not yet fully realised, hybrid approaches already show promising results. As quantum hardware matures, these techniques may enable exploration-driven engineering paradigms and redefine optimisation workflows.

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