Advanced Engineering Informatics 69 (2026) 103960

Contents lists available at ScienceDirect

Advanced Engineering Informatics

journal homepage: www.elsevier.com/locate/aei

Full length article

Quantum and quantum-inspired computing in civil engineering

Joern Ploennigs [a],*, Kay Smarsly [b], Markus Berger [a], Kosmas Dragos [b], Martin Kliesch [b]

[a] University of Rostock, Justus-von-Liebig-Weg 2, Rostock, 18059, Germany
[b] Hamburg University of Technology, Blohmstraße 15, Hamburg, 21079, Germany

ARTICLE INFO

Keywords:
Quantum computing
Quantum-inspired computing
Civil engineering
Research directions

ABSTRACT

Quantum computing is expected to offer solutions to computational problems that are otherwise computationally intractable. Although the core technology is still being developed, quantum-inspired computing already has been offering practical advantages for several computationally challenging problems. Despite the promising potential of both quantum computing and quantum-inspired computing, applications in civil engineering remain underexplored. This study aims to lay the foundation for future adoption by introducing the fundamental principles of quantum computing and quantum-inspired computing and by conducting a multivocal literature review. The review provides insights into the current research landscape in civil engineering and offers a detailed analysis of potential use cases and application areas. The findings are expected to serve as a foundation for guiding future research endeavors and practical deployments of quantum computing and quantum-inspired computing in civil engineering, as these technologies continue to mature.

1. Introduction

Quantum computation (QC) is an emerging computational paradigm that leverages the principles of quantum mechanics to potentially solve complex problems more efficiently than conventional computing. The principles open promising ways to solve computationally complex problems in civil engineering, including numerical calculations, simulations, optimizations, and machine learning problems. Despite regular news and encouraging roadmaps [1–4], quantum technology is still in its early research stages. Several practical challenges remain unaddressed that make large-scale applications unlikely to emerge in the near future.

In response to the current limitations of quantum technology, quantum-inspired computing (QiC) has emerged as a promising alternative. QiC uses algorithms that are derived from ideas of quantum computing, albeit capable of running on conventional computers. QiC offers the potential to expedite certain calculations, while also enabling the preliminary testing of problem formulations in civil engineering that are amenable for solution with actual quantum computers in the foreseeable future.

Civil engineering often involves complex numerical analyses that demand innovative computational approaches to achieve optimal solutions. Several analysis and assessment tasks entail solving complex equation systems whose scalability is restricted in conventional computing methods [5–7]. In this direction, QC & QiC offers advanced data analytics and optimization capabilities that could enhance both technical and managerial processes. As a result, the integration of QC & QiC into civil engineering holds the potential for revolutionizing the field of civil engineering, facilitating efficient, sustainable, and resilient infrastructure development in an increasingly complex world.

This paper will discuss the current state of the art and future prospective of quantum computing and quantum-inspired computing in civil engineering, which has yet to be sufficiently explored. In particular, the current computational challenges in civil engineering will be first discussed, and the research significance will be highlighted in the next section. Then, the concepts, benefits and challenges of quantum computing and of quantum-inspired will be introduced in Sections 3 and 4, respectively. Thereupon, the multivocal literature review will be presented in Sections 5 and 6, from which research challenges and potential use-case areas will be derived in Section 7.

2. Research significance

Civil engineering (CE) has increasingly been relying on computationally intensive methods that push the limits of classical computing. At the *structural scale*, the growing adoption of high-fidelity finite element analyses (FEA), including nonlinear dynamic analyses and seismic simulations, demands massive computational resources [8]. In the area of *optimization*, large-scale topology optimization, multi-objective structural design, and simulation-based optimization typically require iterative FEA analyses, characterized by prohibitive computational cost for large structural systems [9]. Similarly, *uncertainty*

* Corresponding author.
E-mail address: joern.ploennigs@uni-rostock.de (J. Ploennigs).

https://doi.org/10.1016/j.aei.2025.103960
Received 8 August 2025; Received in revised form 26 September 2025; Accepted 6 October 2025
Available online 15 October 2025

and reliability analysis add to the complexity of computational methods, since probabilistic risk assessments, as well as stochastic and high-dimensional sensitivity studies involve simulations typically ranging from thousands to millions [5]. The high computational cost in uncertainty and reliability analysis is particularly evident in *climate and natural hazard risk assessment*, where Monte Carlo simulations of flood, wind, or earthquake hazards are used to propagate deep uncertainty through coupled hazard–exposure–vulnerability models [10]. Several real-world problems are also inherently *multi-physics and multi-scale*, such as concrete material modeling, coupled hydro-thermal–mechanical simulations, and fluid–structure interaction in wind or tsunami engineering [11]. Finally, *infrastructure-level challenges* such as resilience optimization of transportation networks, digital twins for real-time monitoring further exacerbate computational costs [8,9]. Collectively, the aforementioned challenges underscore the increasing complexity of civil engineering models and the limited scalability of classical approaches, such as statistical models, partial differential equations, and tensor calculus, thus restricting the refinement and fidelity of civil engineering models and analysis results.

The aforementioned challenges may be tackled when accelerating analyses using high performance computers or graphics processing unit (GPUs). Nevertheless, computational bottlenecks still persist, due to the fundamentally sequential or iterative nature of the analyses. For example, sparse linear system solvers, eigenvalue problems, optimization loops, and Monte Carlo sampling can hardly be parallelized because each step depends on the result of the previous step. This so-called *sequential dependency* results in diminishing benefits from parallelization, since, beyond a certain point, adding more processors effects negligible reduction in the overall runtime. In addition, modern deep-learning-based approaches face challenges with sequential dependency due to scalability issues. Specifically, recent studies have been raising concerns that modern deep-learning-based models require lots of computational power, as well as large amounts of training data, which — for surrogate models — is usually simulation data from traditional (classical-computing) approaches [6,10,12].

The computing paradigms of quantum computing and quantum-inspired computing promise to overcome the computational challenges by removing the sequential dependency limitation. None of the above-mentioned studies have either focused on techniques for removing the sequential dependency limitation or recommended such techniques as future work, suggesting either a research gap or implicit concerns regarding the applicability of such techniques. In this paper, the fundamental concepts of QC & QiC will be explained along with application potential to civil engineering problems by mapping use cases to relevant QC & QiC algorithms. In addition, the multivocal literature review will serve to highlight the state of the art and identify open research challenges. The main contributions of the paper are to:

- Explain the difference between QC & QiC
- Identify opportunities and challenges for QC & QiC
- Present a multivocal literature review on QC & QiC in CE
- Discuss relevant use cases for QC & QiC in CE
- Extract research challenges for QC & QiC in CE

3. Quantum computing

Quantum computing differs significantly from traditional computing, as will be shown in this section, in which the fundamentals of QC are introduced. It should be noted that this section is not intended to provide a comprehensive background of quantum mechanics.

3.1. The basic idea of quantum computation

The input and output of a classical computation are represented by bits, which take on values of either 0 or 1. The bits are processed using logical gates, such as the universal “NOT-AND” (NAND) gate. The computational framework is grounded in the Church-Turing thesis, which states that any effectively computable function can be represented by a Turing machine or an equivalent system of logical operations.

QC can be represented in a similar way, with the quantum version of a bit being termed *qubit*. Unlike states of classical bits, qubit states are not restricted to 0 and 1, but may assume *superpositions* thereof. Superpositions are known from wave mechanics; e. g., as the side of a string instrument can be in the superposition of several frequencies, a qubit can be in the superposition of the two basic states 0 and 1 with different amplitudes,[1] which describe qubit states. The same principle holds for n qubits: Each state is described by 2^n amplitudes, one for each of the 2^n possible 0/1-combinations of length n. The large state space allows quantum computers to encode and process high-dimensional information, forming the basis for potential computational advantages.

The computations in QC are based on a set of elementary operations, named *quantum gates*. The gates enable the decomposition of complex algorithms, analogous to how classical computations are built from logic gates such as NAND. However, quantum gates, operating on high-dimensional qubits, can transform multiple components of a quantum state simultaneously in a single step, which enables massive parallelization of computations. As a result, complex computational problems can, in principle, be solved more efficiently compared to traditional computers, particularly if the number of qubits is sufficiently large [13].

One of the first major breakthroughs that has highlighted the *quantum speed-up* is the factorization of large integers. The inability of classical algorithms to factor integers efficiently has been used as a basis by crypto-algorithms, such as the Rivest-Shamir-Adeleman (RSA) cryptosystem, to secure data. However, Peter Shor has proposed an efficient quantum algorithm for integer factorization [14], leading to the assumption that quantum computers will break RSA and similar crypto-algorithms in the future. Nonetheless, the theoretical advantage of quantum computers has yet to be realized in practice, primarily due to the technical challenges associated with accurately controlling and maintaining large numbers of qubits. As a result, the practical computational advantage of QC has yet to be demonstrated and would only be meaningful if exponential — or at least superpolynomial — speed-up over classical approaches were provided.

3.2. Quantum computing variants

The technical challenges around controlling qubits have created a landscape of quantum hardware that uses a variety of physical effects, potentially serving as a *platform* for quantum computation, e. g., superconducting qubits, trapped ions, or cold atoms in optical lattices. The variety of physical effects reflects similar past hardware trends from traditional computers, starting from early approaches based on electrical relays and culminating into microchips.

Quantum hardware development faces several intertwined challenges: On the one hand, quantum algorithms require large numbers of qubits and connecting quantum gates. This requirement is often detrimental to quantum hardware, since the number of qubits and quantum gates increases the noise in computations. Since noise accumulates during a quantum computation, either (i) the quantum computation must be finished before too much noise has accumulated, or (ii) a way to correct errors incurred by the noise needs to be found. The former approach is followed in the so-called noisy and intermediate scale quantum (NISQ) era [15], where qubit numbers are rather limited to a few hundred. The second approach is followed by what is called fault-tolerant quantum computing (FTQC), where errors occurring during a quantum computation are identified and reversed using quantum error

[1] The amplitudes are complex numbers with two real parameters being redundant, one for a normalization condition and one for a global phase freedom.

correction [16]. Currently, the NISQ era is prevalent, and the available quantum hardware is limited by noise, which prevents long calculations with a large number of qubits.

In terms of computational analysis, various types of NISQ algorithms have been introduced over the years [17]. One popular NISQ approach, targeted at combinatorial optimization, is *quantum annealing* [18], which solves problems that consist of finding an (approximate) global minimum of a cost function with binary variables heuristically, thus giving rise to the combinatorial character of optimization. Specialized hardware for quantum annealing has been proposed, termed *quantum annealers*, first by D-Wave Systems in 2011 [19], representing an extension of adiabatic quantum computing [20]. The hardware has since been extended to allow for solving large-scale problems. In adiabatic quantum computing, an optimization problem is encoded into the energy landscape of a quantum system. To solve the optimization problem, the quantum system is first initialized in the ground state (i.e., lowest energy state) of a trivial cost function at near-zero temperature. Then, the parameters of the quantum system are slowly changed to represent the cost function of interest. Provided that the change is performed slowly enough, the quantum system remains approximately at zero temperature, corresponding to the optimal value of the cost function. A readout of the quantum state then yields an approximate solution to the optimization problem.

Another general NISQ-approach is the group of variational quantum algorithms (VQAs), i.e. hybrid classical-quantum approaches that combine QC with traditional optimizers to slowly modify parameters iteratively until an optimal solution is reached. Originally, VQAs had been suggested for solving combinatorial optimization problems [21] as well as the electronic structure problem in quantum chemistry and condensed matter physics [22]. The research approaches on VQAs have revealed limitations, mainly in the classical optimization part, which can hardly converge due to local minima and barren plateaus [23]. However, the capability of VQAs to solve eigenvalue problems in equation systems allows usage in other quantum algorithms [24], thus enabling several applications in quantum machine learning.

Another example of NISQ-based approaches is referred to as *analogue quantum simulations* [25], which are typically employed to simulate one quantum system using another. For example, cold atoms in optical lattices may be used to simulate the behavior of electrons in a solid. However, analogue quantum simulations are generally considered less relevant for applications in civil engineering, as quantum effects are minor.

Finally, the challenge of NISQ-based approaches is the limited number of qubits with a manageable noise level [26]. FTQC allows for longer quantum algorithm runtimes that support a large number of quantum algorithms, referred to as *universal quantum computer*. For details, the interested reader is referred to [27].

3.3. Potentials

The main application areas of QC in civil engineering include simulation, machine learning, and optimization. In what follows, the potential for employing QC in the application areas is discussed.

Simulation is a key application area of quantum computers, particularly for quantum-level systems, such as Hamiltonian dynamics and ground-state preparation. Ongoing research has been exploring many-body quantum systems using quantum computing [28], with applications in chemistry, such as molecular structures [29] and chemical reactions [30], which may lead to new approaches for discovering novel materials [31]. The goal is to use the precision of quantum simulations for improving predictions of molecular behavior so as to benefit drug discovery, materials design, and catalysis [32]. A notable recent advancement is the simulation of 2D transverse-field Ising model dynamics [33].

Machine learning is another main application area for QC with promising approaches, such as quantum kernel methods for classification tasks, which have exhibited exponential speed increases compared to classical algorithms [34]. Other quantum algorithms, such as quantum phase estimation (QPE) [35] and the quantum Fourier transform (QFT) [36], are subroutines of Shor's algorithm for integer factorization [14] and have applications in machine learning, as does the Harrow–Hassidim–Lloyd (HHL) algorithm for solving linear equations [37]. By extension, QPE and QFT may also be used for numerical problems in civil engineering. Moreover, quantum algorithms for neural networks have been an active research area [38,39]. Quantum computing has also been investigated as a means to enhance classical algorithms, particularly in the context of tensor operations and dot-product calculations [40,41].

Optimization, a further main application area relevant to civil engineering, includes methods based on quantum annealing (QA), variational quantum eigensolver (VQE), and quantum approximate optimization algorithm (QAOA), designed to solve combinatorial optimization problems and potentially outperforming classical methods [21,42,43]. A primary class of combinatorial optimization problems is known as quadratic binary optimization (QUBO) problems. The goal of QUBO is to find the best possible combination of binary variables that minimizes a mathematical function. Several NP-hard problems in optimization can be formulated within the QUBO framework [44], such as the traveling salesman problem, graph partitioning, and job scheduling. Given its importance with respect to the current study, a QUBO example in the civil engineering context will be presented in the following subsection.

3.4. QUBO example within a QC context

In this subsection, an example of the QUBO problem involving the optimization of the placement of two structural health monitoring sensors on a bridge for efficient damage detection is presented [45]. Optimally placing a single sensor is relatively straightforward, following the evaluation of several potential positions and picking the position that yields the richest information on damage detection. The optimal placement of two sensors increases the complexity, since the position of one sensor depends on the position of the other sensor when aiming to maximize the information on damage detection. In this context, the placement of two sensors can be recast as an optimization problem with combinatorial dependency between decision variables, which is typical for QUBO problems. To formalize the optimization problem, each of the n candidate locations is represented by a binary variable $x_i \in \{0,1\}$, which indicates whether a sensor is placed at the location or not. The optimization objective is then to choose exactly two locations x_i, x_j that maximize the damage detection performance, given a matrix W that defines the cost for each location pair. The search space can be reduced by excluding identical indices ($i = j$) and by treating sensors as interchangeable ($i < j$). To enforce the constraint that exactly two sensors are placed, a quadratic penalty term is added. Since QUBO problems are unconstrained, this constraint is encoded as $(\sum_i x_i - 2)^2$, scaled by a large factor λ. The resulting QUBO problem is:

$$\min \sum_{i<j} W_{ij} x_i x_j + \lambda * (\sum_i x_i - 2)^2 \tag{1}$$

The formalization illustrates how a simple sensor placement problem can be represented as QUBO. The problem quickly becomes computationally challenging when more than two sensors must be placed in a high-resolution grid with a large number n of potential sensor locations, especially if determining the weights W requires running FEM simulations.

An efficient solution to the aforementioned problem using quantum computers will be covered in Section 4.2. Nevertheless, quantum computers are not expected to solve all computationally complex problems dramatically faster than traditional computers. For instance, NP-hard problems are still expected to exhibit exponential worst-case runtimes. In this regard, improvable problem classes, such as the discussed NP-intermediate problems, must be identified [46].

3.5. Challenges

Adopting quantum computers is hardly straightforward, which essentially explains why quantum computers have not been available yet in practice. In this subsection, the challenges of quantum computers are briefly discussed by means of three aspects, (i) error mitigation and correction, (ii) QC knowledge for usage, and (iii) quantum advantage.

Error mitigation and correction: Large quantum devices are inherently noisy, and the noise must be reduced during quantum computations. In the NISQ era [47], the reduction is achieved using *quantum error mitigation (QEM)* [48]. In particular, errors are reduced by repeating quantum computations multiple times and performing post-processing on the results. The number of repetitions required for each quantum computation must be sufficiently large to enable the extraction of reliable statistics for error mitigation, which introduces a mild exponential overhead. *Quantum error correction (QEC)*, by contrast, uses several physical qubits to represent fewer logical qubits in the form of a quantum error correction code [49], allowing errors to be detected and, in many cases, corrected, ultimately enabling fault-tolerant quantum computing (FTQC). Nonetheless, QEC requires specific correction codes for each quantum gate, and the total overhead of additional qubits often turns out to be large in practice, particularly for small quantum computers. Finally, QEC and QEM can be combined, and the balance between error mitigation and correction represents a trade-off between reliability and scalability.

QC knowledge for usage: Due to the fundamental difference in representing information as a qubit and the behavior of quantum gates, it is not possible to simply cross-compile existing code for QC. Instead, special quantum programming languages have been developed that often require a good understanding of fundamental computing concepts in QC [50]. Thankfully, experts have been developing problem-specific frameworks, e. g. for quantum chemistry, machine learning or optimization problems, which lower the entry barrier to utilize quantum computers. However, the uptake of the frameworks in practice will take time. The development of graphics processing unit (GPU) computing offers parallel computing capabilities that may provide valuable insights. While modern computers are equipped with GPUs boasting hundreds to thousands of cores—far more than traditional CPUs—GPUs have not replaced CPUs for two reasons: First, problems are not easily parallelizable and thus not well-suited for GPUs. In fact, most problems are highly sequential, rendering central-processing-unit-derived solutions more efficient. Second, problems need to be specifically implemented for the GPU in dedicated frameworks, which may be time-consuming. For example, NVIDIA introduced CUDA in 2007 [51], yet its applications in civil engineering software remain limited [52]. Instead, it took several years for the completely different area of neural networks to exploit GPUs to scale deep learning, which now also has a decisive impact on civil engineering.

Quantum advantage: Quantum computers are not well suited for most common problems that are solved with the help of computers and are therefore neither expected to outperform nor replace traditional CPUs in basic applications. Each specific case where a quantum computer is proven to outperform a traditional computer (exponentially) is called *quantum advantage*. Although in theory multiple problem formulations and algorithms have existed for many years, such as Deutsch-Jozsa [53], Shor [14], and Grover [54], a practical demonstration of quantum advantage has yet to be achieved. In this direction, ongoing research aims to demonstrate quantum advantage for relevant problems in civil engineering.

4. Quantum-inspired computing

Research into quantum computing has yielded useful insights into alternative ways of solving complex problems. Several insights have inspired algorithms that also run on conventional hardware or have led to new hardware solutions tailored to solving specific optimization problems, referred to as *quantum-inspired computing (QiC)*. While QiC is, in fact, classical computing that involves new reformulations of existing problems, its benefits for solving real-world problems have already been established.

4.1. Potentials

With potential relevance to civil engineering, quantum-inspired algorithms, e.g., encompass low-rank matrix reconstruction for compressive sensing, as introduced by Gross [55], and specific training methodologies for deep Boltzmann machines, as discussed by Wiebe et al. [56]. The latter are also important in algorithm theory, where efficient classical variants of quantum algorithms have been developed in a process coined "de-quantization" [57].

With respect to *simulation*, matrix product state (MPS) may be used to represent discretized functions and linear operators, as well as linear algebra routines, in a computationally efficient way. The representations have been used to develop powerful algorithms for solving complex partial differential equations (PDEs) in computational fluid dynamics (CFD) simulations [58,59], by permitting denser discretizations of the problem space.

Regarding *machine learning*, tensor networks represent another area of QiC research, primarily employed for modeling and simulating quantum systems on conventional computers. Complex tensor computations on conventional computers have witnessed performance enhancements in the past years [60]. Tree tensor network (TTN) are an extension of MPS and offer advantages in modeling deep neural networks, due to the capacity of managing high-dimensional data, thus enabling the construction of small networks with high information density, as corroborated by Felser et al. [61], by Wall & D'Aguanno [62], and in the meta-study from Wang et al. [63].

In *optimization*, QUBO problems are again highly relevant for mapping problems to quantum-inspired computation. QUBO problems are reformulated as Ising problems, which are closer to how many solvers (called Ising machines) function natively. The solvers range from classical heuristics, such as simulated annealing, to specialized integrated circuits (without quantum effects). Some recent solvers incorporate quantum-inspired algorithms, such as simulated bifurcation, or physical (usually optical) elements that utilize limited quantum effects [64–70]. Another popular method is simulated quantum annealing, which adapts the concept of tunneling from quantum annealing into the classical simulated annealing method. Simulated quantum annealing is essentially a QiC-variant that may outperform simulated annealing in certain cases [71].

4.2. QUBO example within a QiC context

To highlight the differences between QC and QiC approaches and to clarify how QiC can be applied to civil engineering, the QUBO example from Section 3.4 is revisited. Translating the QUBO problem from Eq. (1) into an Ising model requires substituting the binary variable $x_i \in \{0,1\}$ with an Ising spin $s_i \in \{-1,1\}$ using $x_i = (s_i+1)/2$. After the substitution, the quadratic and linear terms of the QUBO are mapped into the Ising Hamiltonian by shifting the weight matrix W as well as the penalty contributions into a matrix J (quadratic couplings) and a vector h (local fields). The corresponding Ising formulation is:

$$\min \sum_{i<j} J_{ij} s_i s_j + \sum_i h_i s_i \tag{2}$$

This Ising model can be entered into different solvers. A simulated annealing method makes random local alterations to the spins in the Ising Hamiltonian, while the overall energy of the quantum system decreases. The decrease continues until an energy ground state is reached. Simulated quantum annealing works in a similar way, but random local alterations can occasionally take the form of bigger global jumps. Finally, with quantum annealing, the QUBO or Ising coefficients are directly encoded into the state of a quantum chip, which can use physical superpositions and tunneling directly to explore the way to an optimal ground state.

Table 1
Comparison between traditional computers (TC), noisy and intermediate-scale quantum computing (NISQC), fault-tolerant quantum computing (FTQC), and quantum-inspired computing (QiC)

Criteria	TC	NISQC	FTQC	QiC
Availability at scale	High	Low	No	Med
Improvement potential	Low	Med–High	High	Med
Demonstrated improvement	–	No	No	Med
QC knowledge	None	High	High	Med
Use cases	Wide	Specific	Specific–wide	Very specific

4.3. Challenges

The challenges in adopting QiC for CE problems are illuminated in this subsection, sorted by (i) specific use cases, (ii) QC knowledge for usage, and (iii) computational advantage. An overview of the challenges compared among different computing concepts is provided in Table 1.

Specific use cases: Quantum-inspired computing is more restricted in terms of use cases than universal quantum computers, focusing primarily on quantum annealing and tensor networks. For example, Shor's algorithm requires full quantum computing capabilities and is not expected to be compatible with any equivalent classical algorithm. Use cases that benefit from quantum-inspired computing might still achieve even greater performance on quantum computers, if available.

QC knowledge for usage: To fully utilize the benefits of quantum-inspired computing in quantum annealing or tensor networks, a good understanding of the underlying tensor decompositions is still required. The requirement poses challenges for widespread adoption by practitioners. Frameworks that simplify usage exist, such as [58], but hardly constitute drop-in replacements for existing frameworks.

Computational advantage: The computational benefit of quantum-inspired computing can be demonstrated easily, since traditional computers or dedicated hardware for quantum annealing can be used. In several benchmark studies, quantum-inspired Ising machines have outperformed other conventional approaches in QUBO problems involving up to 100,000 variables [72–74]. Despite the promising results, QiC is still based on classical computation and is therefore not expected to offer the same advantages as QC.

5. Literature review

The review is a multivocal literature review (MLR), encompassing a systematic literature review (SLR) and a gray literature review (GLR), and it aims to illuminate the current state of research and development, as well as potential use cases of quantum computing and quantum-inspired computing in civil engineering. The methodology, shown in Fig. 1, involves three phases with multiple steps, (a) the *planning phase* defines the objectives and procedures of the MLR; (b) the *execution phase* collects the studies and extracts data according to the objectives; and (c) the *reporting phase* analyzes the data to derive results and discuss recommendations.

In the first step, two research questions are formulated based on the objectives of the MLR:

- RQ1: What is the current state of research and development of quantum computing and quantum-inspired computing in civil engineering?
- RQ2: What are potential application areas and use cases within civil engineering, in which quantum computing and quantum-inspired computing may outperform traditional approaches?

In the second step, the search strategy is defined. To search for the white literature, the bibliographic database "Scopus" [75] is selected because of its multidisciplinary coverage, consistent metadata quality, and advanced fielded search options. Scopus supports a structured query logic and standardized field scoping, allowing queries to be restricted (e.g. to article titles, abstracts, and author keywords, as conducted in this study) together with exportable result sets and stable identifiers. To retrieve the gray literature, the "Zenodo" [76] repository is selected due to its broad collection of non-peer-reviewed research outputs, including industry developments, project deliverables, reports, and white papers. Zenodo supports precise, reproducible retrieval via advanced phrase/Boolean queries, field search, range filtering, and explicit ranking options; its documented search syntax and public REST API enable auditable queries and repeatable exports. For the GLR, the searches have been limited to openly accessible records categorized as publications and available as full-text PDF or DOCX files. Regarding the limitations of using the abovementioned databases, risks include language bias (English-only screening), coverage bias (Scopus may under-index some regional venues; Zenodo is non-exhaustive and heterogeneous in document quality), and temporal volatility of gray records. The risks are addressed by (i) documenting search strings, filters, and retrieval dates, (ii) applying explicit inclusion, exclusion, and quality-assessment criteria, which will be presented in the following paragraphs, (iii) de-duplicating across sources, and (iv) conducting targeted backward/forward snowballing from included items to close coverage gaps. For versioned gray records, the exact version and access date are reported, and non-English items are logged with exclusion reasons to make the language constraint explicit.

Table 2
Search strings and results related to QC & QiC for the SLR within article title, abstract, and keywords and for the GLR within the whole document.

No.	Search string	Results SLR	Results GLR
$S_{1,1}$	"quantum" AND "computing"	43,289	2158
$S_{1,2}$	"quantum" AND "computing" AND "engineering"	2370	539
$S_{1,3}$	"quantum" AND "computing" AND "civil" AND "engineering"	23	16
$S_{2,1}$	"quantum-inspired" AND "computing"	900	53
$S_{2,2}$	"quantum-inspired" AND "computing" AND "engineering"	63	24
$S_{2,3}$	"quantum-inspired" AND "computing" AND "civil" AND "engineering"	1	1

Table 3
Selection Criteria: IC—Inclusion; EC—Exclusion; QAC—Quality assessment.

ID	Criteria
IC_1	The study has been published in English
IC_2	The study has been published in the period between 2015 and 2025
IC_3	The study is related to the area of engineering (only SLR)
EC_1	The full text is not available
QAC_1	The objectives of the study are clearly stated
QAC_2	The limitations of the study are clearly stated
QAC_3	The methodology of the study is stated
QAC_4	The study contributes to answering one or more of the research questions

The search strategy is divided into "quantum" and "quantum-inspired" combined with the common term "computing". The search is narrowed down from a general landscape of studies in QC and QiC to studies in the field of engineering, and it is then further limited to civil engineering. Table 2 shows the search strings and results related to QC and QiC. The numbers for the SLR are within article title, abstract, and keywords and for the GLR within the whole document. The time series for the SLR, indicating the academic publication output, are shown in Fig. 2.

In the third step, the inclusion criteria (IC), exclusion criteria (EC), and quality assurance criteria (QAC), shown in Table 3, are defined to systematically identify relevant and high-quality studies for inclusion in the literature review, ensuring that the selected publications meet the objectives and address the formulated research questions.

In the fourth step, the data extraction methods are defined and implemented in a structured data sheet, including the title, type, year,

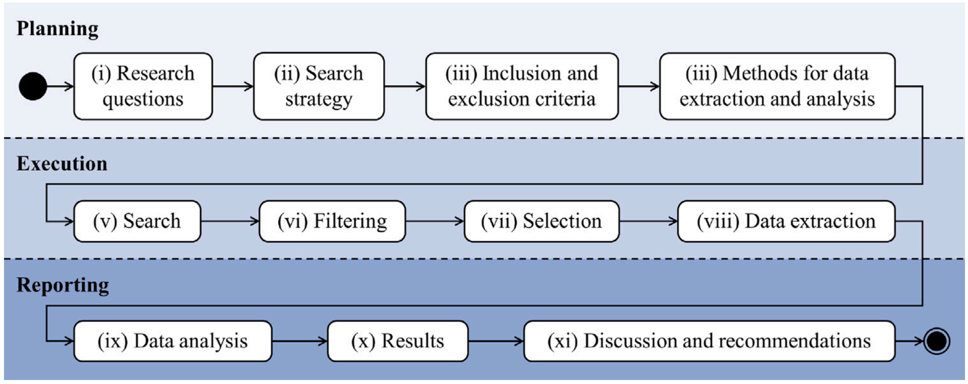

Fig. 1. Overview of the research methodology.

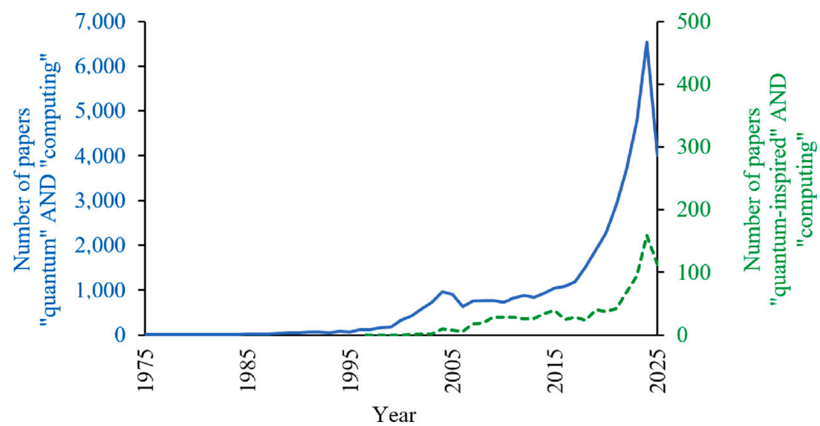

Fig. 2. Publication output in quantum computing (search string $S_{1,1}$) and in quantum-inspired computing (search string $S_{2,1}$).

discipline (to gain an overview of the selected studies), and the thematic scopes of the studies. Statistical analysis is employed as the data analysis method. Upon completion of the planning phase, the execution phase is carried out by applying the defined criteria and methodologies to the data sheet in steps (v) to (viii).

The search for the SLR on “quantum computing” yields a total of 43,289 studies that are narrowed down to 2,370 studies related to engineering and 23 studies related to civil engineering. Furthermore, 900 studies on “quantum-inspired computing” are narrowed down to 63 studies related to engineering, and one study related to civil engineering is found [77]. The GLR results in a total of 2,158 studies on “quantum computing” that is filtered down to 539 studies related to engineering and 16 studies related to civil engineering. Furthermore, 53 studies on “quantum-inspired computing” are narrowed down to 24 studies related to engineering and one to civil engineering [78]. However, this particular source does not meet the GLR inclusion criteria summarized in Table 3, as it is not an industry development, project deliverable, report, or white paper (which the GLR was devised to find), but rather an article in a non-Scopus-indexed journal. In addition, five relevant studies are identified from the GLR results through iterative backward snowballing. In the final reporting phase, the extracted data is analyzed (step ix), the results are synthesized (step x), and discussed to draw relevant recommendations (step xi). The results from step (x) are outlined in Section 6, and the discussion and recommendations from step (xi) are presented in Section 7.

6. Results

The following subsections summarize the results obtained from the reporting phase of the MLR (i) on “quantum computing” and (ii) on “quantum-inspired computing”, structured further into white literature from the SLR and into gray literature analysis from the GLR. In response to ***research question 1***, a general observation is that studies aiming to explicitly solving specific civil engineering problems are still rare, but a number of studies have been reported exploring methods from QC & QiC in other engineering disciplines that potentially can be applied to civil engineering. The key papers identified in this review as well as its explicit or potential contributions to civil engineering are summarized in Table 4.

6.1. Quantum computing related to civil engineering

With respect to ***white literature***, the results obtained from the SLR show that quantum computing has been explored across various engineering fields relevant to civil engineering, with potential use cases in civil engineering, as reported, e.g., in [79]. Furthermore, explicit quantum computing use cases in civil engineering are observed; examples include [80,81]. Quantum algorithms, such as Shor’s and Grover’s algorithms, efficiently solve computationally intensive civil engineering tasks, such as structural analysis and optimization. Quantum machine learning, particularly quantum support vector machines, handles large-scale data for infrastructure planning and monitoring. Nanomaterials, including graphene oxide and carbon nanotubes, leverage quantum mechanical properties to enhance tensile strength, durability, and energy efficiency. Quantum simulations support modeling of material behavior at the atomic scale, improving the design and resilience of construction materials. Quantum cryptography secures data communication in large engineering projects, while quantum technologies advance automation through real-time decision-making in civil engineering, enabling, e. g., advanced robotics for material deposition and autonomous monitoring. A recent study demonstrated a variational quantum neural network as a surrogate model for static structural analysis, underscoring the growing impact of quantum algorithms in civil engineering computations.

Regarding ***gray literature***, which primarily reflects the current state of industrial practice rather than academic research, quantum approaches have been reported that explicitly address civil engineering use cases [82,83] or that can potentially be transferred to civil engineering [84]. Specifically, the exploration of quantum principles, such as superposition and entanglement, in information processing and visual perception suggests potential applications in civil engineering, for example, to enhance structural health monitoring and inspection through improved data-driven decision-making [85]. Several companies, including Microsoft [86], IBM [87], Google [88], Intel [89], and Honeywell [90], are actively involved in developing physical quantum computers and quantum algorithms. This work includes quantum algorithms that may be applied to optimize construction processes, quantum sensors to advance infrastructure monitoring, and quantum-enhanced simulations for structural optimization and materials science. Notably, in 2024, the U.S. Department of Transportation highlighted QC applications for optimizing transportation infrastructure and employing quantum sensors for improved structural health monitoring [45].

6.2. Quantum-inspired computing related to in civil engineering

With regard to ***white literature***, as mentioned previously, studies published specifically to explicitly solving specific civil engineering problems using quantum-inspired computing are rare; examples include [91–95]. However, quantum-inspired computing has been explored in several engineering disciplines, with potential relevance for civil engineering applications, as reported, e. g. in [92,96–99]. In the studies reviewed herein, quantum-inspired algorithms are, e.g., used to enhance the design of materials and structural elements, such as trusses and composite laminates critical in civil engineering, allowing to optimize mechanical properties and resource efficiency, while improving both performance and cost-effectiveness. For instance, a recent study employing a quantum-inspired harmony search algorithm achieved a lighter optimal truss design than conventional evolutionary methods, highlighting the efficiency of quantum-based metaheuristics in structural weight optimization. Transportation systems benefit from quantum-inspired algorithms, e.g., in optimizing railway scheduling, route planning, and train stop arrangements, which may increase passenger flow efficiency and reduce delays in urban transportation networks. In the context of complex transportation planning, a quantum-inspired bi-level algorithm for emergency response network design generates near-optimal road usage plans more efficiently, matching or surpassing classical approaches in solving this challenging problem. Infrastructure monitoring and maintenance is another area where quantum-inspired computing shows promise, as techniques proposed for real-time scheduling and data processing enable more efficient monitoring of civil infrastructure by enhancing the ability to predict and prevent structural failure, contributing to safer and more resilient infrastructure systems.

As for ***gray literature***, QiC explicitly applied to civil engineering use cases can hardly be found. However, use cases reported in related disciplines with transfer potential are observed. For example, industry case studies suggest tangible benefits: NEC Corporation deploys a quantum-inspired optimization system for daily maintenance-part logistics in Tokyo, automating route plans (a problem space of 10^{753} combinations) and significantly increasing operational efficiency while reducing costs and emissions [100]. Likewise, quantum-inspired techniques are being explored in smart city applications. For example, simulation studies report that quantum-inspired optimized traffic signal timing and public transit scheduling can reduce congestion and improve travel times [101]. Projects have been reported that use quantum ML to improve storm prediction accuracy (relevant to large construction projects) by processing big datasets of satellite images, utilizing, e. g., Grover's algorithms and quantum neural networks [84].

7. Application areas and use cases of QC and QiC in civil engineering

This section concerns ***research question 2*** and — building upon on the results presented in the previous section — structures potential application areas and use cases in civil engineering, in which quantum computing and quantum-inspired computing may outperform conventional computing, thereby illustrating the opportunities, challenges, and visions of quantum computing and quantum-inspired computing in civil engineering.

A broad wealth of use cases in civil engineering is analyzed, spanning the application areas "simulation", "optimization", and "machine learning". The outcome of the analysis is a mapping that aligns civil engineering disciplines and the application areas with the potential applicability of quantum computing and quantum-inspired computing, as shown in Fig. 3. For example, regarding the application areas with respect to quantum-inspired computing, the main QiC algorithms are identified as (i) matrix product states used to efficiently solve differential equations ("simulation" application area), (ii) quantum annealing to solve QUBO problems ("optimization" application area), and (iii) tree tensor networks to achieve more compact deep learning networks "machine learning" application area). The applicability of the QiC algorithms within the civil engineering disciplines is categorized into three levels: "high" (indicated by bold lines), "moderate" (indicated by dotted lines), and "low' (no indication), with expanded details to follow in the subsequent discussion. Specifically, the civil engineering disciplines and the opportunities, challenges, and visions of potential quantum computing and quantum-inspired computing applications will be discussed in the following paragraphs.

Structural analysis and design, as well as related and sub-disciplines (such as structural health monitoring), largely rely on numerical methods for simulating and analyzing the behavior of engineering structures under various loads. Regarding numerical methods, two main approaches are typically employed, (i) rigid body models, which idealize structures as stiff elements connected by joints, and (ii) finite element analysis (FEA), which discretizes structures into meshes for detailed stress, strain, and displacement analysis. High accuracy in FEA requires significant computational resources, as the number of elements directly impacts the complexity of the calculations. Both numerical modeling approaches may benefit from QC and QiC methods. FEA often relies on complex dynamic equation systems, where quantum kernel methods and the QFT can improve computation of complex scenarios. Quantum-inspired MPS methods offer potential for enhanced discretization, allowing higher-resolution models. Moreover, optimization problems are common in structural analysis and design to determine the optimum balance between structural integrity and material efficiency. The optimization approaches are often based on nonlinear programming, genetic algorithms, and simulated annealing, i. e. the application of quantum annealing is promising, with potential applications in generating QUBO problems for more efficient solutions.

Hydraulic engineering typically utilizes CFD instead of FEA to simulate the dynamics of fluids, including turbulence and fluid–structure interactions in systems such as rivers, dams, and water distribution networks. Gourianov et al. [58] demonstrated the application of quantum-inspired methods in CFD, releasing an open-source MATLAB library for the MPS approach proposed in the study. In addition, hydraulic engineering employs network models for pipes and rivers, suitable for graph-based optimization problems. Similar to FEA, different numerical computation approaches from QC apply in this area. Speziali et al. [106] have explored sensor placement in water networks using an adiabatic quantum computing (AQC) method, effectively mapping the problem to a QUBO framework and demonstrating how QC can be successfully applied in CFD.

Urban and traffic planning utilizes simulations for pedestrian and vehicular movement within buildings and transportation networks,

Table 4
Key papers identified from the SLR and GLR with main civil engineering application area(s) and civil engineering use case(s), either explicitly addressed in the study or potentially transferable to civil engineering.

Author(s) and Year	Source	Application area(s)	Explicit (E) or potential (P) civil engineering use case(s)
Ajagekar and You (2025) [80]	SLR (QC)	Optimization, machine learning	Decarbonization of building operations with adaptive model predictive control using quantum approximate optimization algorithms *(E)*
Chang et al. (2024) [99]	SLR (QiC)	Optimization, simulation	Optimizing construction site logistics using quantum-inspired Ising machines *(P)*
Dueñas-Osorio et al. (2018) [95]	SLR (QiC)	Optimization, simulation	Reliability and resilience assessment of lifeline infrastructure networks based on quantum-inspired tensor network Boolean satisfiability counting *(E)*
Karahalios et al. (2024) [91]	SLR (QiC)	Optimization	Earthquake evacuation planning using quantum-inspired bilevel optimization algorithms *(E)*
Kaveh et al. (2020) [94]	SLR (QiC)	Optimization	Truss weight optimization under stress and displacement constraints using quantum-inspired enhanced colliding bodies optimization *(E)*
Lee et al. (2023) [93]	SLR (QiC)	Optimization, simulation	Discrete truss topology and member sizing optimization using a quantum-inspired harmony search *(E)*
Leijnse (2025) [82]	GLR (QC)	Simulation, optimization	Water distribution system optimization using quantum annealing *(E)*
LeMaster and Vakhari (2024) [83]	GLR (QC)	Optimization, simulation	Network optimization for transportation logistics using quantum annealing *(E)*
Liu, Jinyi et al. (2024) [92]	SLR (QiC)	Optimization, machine learning, simulation	Detection of underground voids and sinkholes using quantum gravimetry *(E)*
Liu, Yunya et al. (2024) [102]	SLR (QC)	Optimization, simulation	Determining the natural frequencies of structural elements using quantum eigensolvers *(E)*
Milutinović and Salom (2023) [103]	SLR (QC)	Machine learning, simulation	Structural Health Monitoring of bridges and buildings using quantum mechanical computing *(E)*
Pérez Armas et al. (2024) [81]	SLR (QC)	Optimization	Project scheduling and resource allocation using quantum annealing *(E)*
Salloum et al. (2025) [79]	SLR (QC)	Optimization	Construction site logistics optimization under capacity constraints using quantum annealing *(P)*
San Martín and López (2024) [104]	SLR (QC)	Simulation, optimization	Optimal sensor placement for structural health monitoring using quantum approximate optimization *(E)*
Schetakis et al. (2025) [105]	SLR (QC)	Machine learning	Construction site traffic flow optimization using quantum neural networks *(E)*
Sudha et al. (2023) [84]	GLR (QC)	Machine learning, optimization	Automated crack detection in concrete structures using quantum neural networks *(P)*
Wang & Wang (2024) [96]	SLR (QiC)	Optimization, simulation	Layout optimization of steel bracing systems using quantum-behaved particle swarm optimization *(P)*
Wulff et al. (2024) [98]	SLR (QiC)	Optimization, simulation	Optimizing carbon-fiber laminate stacking sequences for structural components using variational quantum algorithms *(P)*
Yevseiev et al. (2022) [97]	SLR (QiC)	Optimization, machine learning	Construction site scheduling using quantum-inspired optimization *(P)*

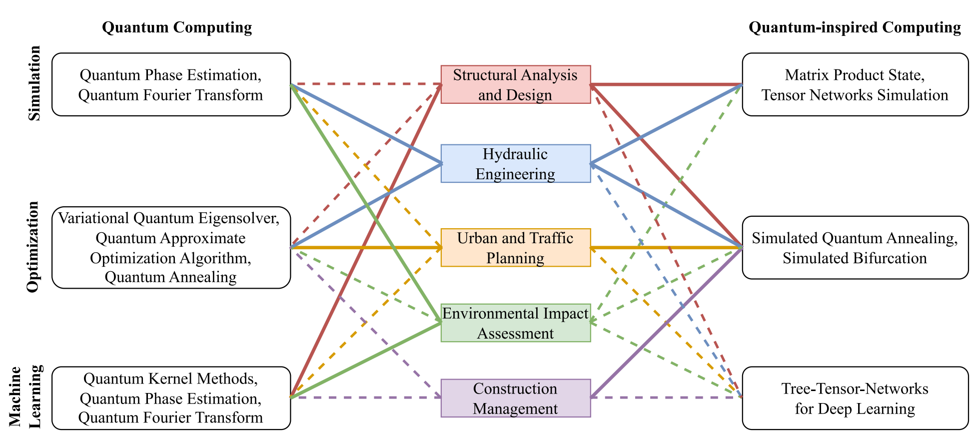

Fig. 3. Overview of engineering disciplines with high (bold), moderate (dotted), and limited (none) applicability potential of QC & QiC.

capturing complex interactions among people, vehicles, and infrastructure. The main challenge in systems deployed for urban and traffic simulation is the stochastic nature of human decision-making, entailing emergent phenomena in people and traffic flows, which introduce stochastic elements less suited to QC & QiC algorithms. However, optimizing traffic network designs is a primary goal, involving network flow optimization or logistic routing problems, both of which can be adapted to quantum-inspired solutions. Additionally, site selection for infrastructure facilities, while geospatial in nature, involves complex decision-making that may also benefit from quantum-inspired approaches, despite the higher complexity of constraints and variables involved.

Environmental impact assessment examines the effects of the built environment on the natural environment, typically employing CFD or FEA methods [107], i. e. areas where tensor networks show promise, as previously discussed. While applications such as simulated annealing have been used in building design for energy efficiency, integrating QUBO remains unexplored. Although many optimization problems in reducing energy consumption relate to scheduling and control, the problems often present limited potential for the application of QC & QiC.

Construction management focuses on optimizing resource allocation and project scheduling, including the efficient distribution of labor, equipment, and materials. The optimization challenges are often conducive to being structured as QUBO problems, rendering QUBO suitable for QC & QiC algorithmic solutions in construction management.

Machine learning has not explicitly been addressed above, as it is widely adopted across all civil engineering disciplines and fundamental improvements are expected in this area by QC & QiC. However, it should be emphasized the specific advantages of quantum computing for machine learning techniques do not fully translate to quantum-inspired computing. Notably, tree tensor networks represent an area where quantum-inspired approaches are considered suitable particularly for developing compact deep neural networks in scenarios with strong interlayer correlations. The insight opens potential, e. g., for applications in surrogate models for FEM/CFD or complex graph neural networks, suggesting a nuanced landscape where QC & QiC could be expected to offer distinct benefits.

8. Summary and conclusions

Despite its prospective advantages, the application of QC & QiC in civil engineering has scarcely been explored. Therefore, in this study, a multivocal review has been conducted to pinpoint potential use cases where QC & QiC may surpass conventional computing approaches. Opportunities, challenges, and visions have been summarized to establish a foundation in preparation for the anticipated advancements and increased accessibility of quantum computers in the field of civil engineering. The review has illustrated the potential of QC & QiC in civil engineering.

Research and development in the field of QC & QiC within civil engineering remains in an early stage. The vast majority of studies focus on optimization approaches, primarily using quantum-inspired evolutionary algorithms (particularly genetic algorithms), while a few studies address simulation and machine learning. On the one hand, the frequent use of QUBO problems highlights optimization as a promising and currently accessible application area for QC & QiC. On the other hand, there is significant untapped potential to expand the application of QC & QiC to simulation and machine learning in civil engineering.

The use case mapping in this paper shows the versatility and wide-reaching potential of enhancing civil engineering disciplines such as structural analysis and design, hydraulic engineering, urban and traffic planning, environmental impact assessment, and construction management. The applicability of QC & QiC across the use case areas varies from fundamental numerical improvements to specific use case solutions. The preliminary conclusions with respect to the application areas "simulation", "optimization", and "machine learning" are summarized as follows.

- *Simulation:* Finite element analysis and computational fluid dynamics represent some of the most computationally intensive tasks in structural and hydraulic engineering. Quantum computing offers the potential to accelerate the solution of differential equations in the domains. In this context, enhanced discretization techniques, such as matrix product states, are a key enabler. Current formulations are exemplary and rudimentary and do not fully represent the existing complexity. It is recommended to look into using MPS for more complex use cases of FEM for structural stability.
- *Optimization:* Quantum computing has been widely explored for solving optimization problems across various domains. Ongoing research investigates potential speed-ups for specific algorithms. Until large-scale quantum computing becomes practical, quantum-inspired computing offers viable hardware acceleration. The availability of QiC and the ability of several NP-hard problems to be mapped into QUBO problems [44] renders QiC an attractive field to recast common engineering problems as QUBO problems.
- *Machine learning:* The most significant promise of quantum computing lies in the acceleration that may be achieved through quantum kernel methods for classification tasks. Furthermore, many algorithmic components of modern machine learning, such as eigenvalue problems, feature extraction, model training, and dimensionality reduction, may be enhanced through hybrid quantum approaches, such as VQA or QAOA. The enhancement is expected to be conducted within existing ML frameworks with no direct action necessary in civil engineering. However, continuous investigation into the applicability of specific quantum-enhanced models for CE problems, such as quantum principal component analysis, quantum neural networks, and generative adversarial networks, is recommended to prepare for future advancements.

In conclusion, quantum-inspired computing currently offers practical solutions for optimizing QUBO problems and enables improved discretization in FEA and CFD simulations. Quantum computing, once widely available, holds the potential to address more fundamental computational challenges across all civil engineering use cases, particularly through its advancements in machine learning. Given the current technological limitations, it is advisable to continue exploring the applicability of QC & QiC concepts in civil engineering through small-scale, well-defined pilot projects.

CRediT authorship contribution statement

Joern Ploennigs: Writing – review & editing, Writing – original draft, Visualization, Conceptualization. **Kay Smarsly:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Markus Berger:** Writing – review & editing, Writing – original draft, Visualization. **Kosmas Dragos:** Writing – review & editing, Writing – original draft. **Martin Kliesch:** Writing – original draft, Validation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Kay Smarsly reports financial support was provided by German Research Foundation. Martin Kliesch reports was provided by Education Research and Development Foundation. Martin Kliesch reports was provided by Fujitsu Ltd. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors thank Martin Mevissen from IBM Research Europe for his input and review comments on Quantum Computing. The authors also gratefully acknowledge the support offered by the German Research Foundation (DFG) through grant SM 281/33-1. M.K. is supported within the Hamburg Quantum Computing project, which is co-financed by the ERDF of the European Union and the Fonds of the Hamburg Ministry of Science, Research, Equalities and Districts (BWFGB), and by the Fujitsu Germany GmbH as part of the endowed professorship "Quantum Inspired and Quantum Optimization".

Data availability

No data was used for the research described in the article.

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