

Quantum Computing for Energy Systems: A Literature Review and Strategic Assessment

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Summary

This report reviews quantum computing applications in energy systems, focusing on optimization, planning, operation, and decision-making problems. The motivation is the increasing computational complexity of modern power systems, driven by high renewable penetration, stochastic operation, sector coupling, and multi-timescale decision-making, factors that stress classical methods on large-scale mixed-integer, stochastic, and network-constrained problems.

The review concentrates on approaches relevant under current Noisy Intermediate-Scale Quantum (NISQ) constraints, like quantum annealing, variational algorithms including the Quantum Approximate Optimization Algorithm (QAOA), and hybrid quantum-classical workflows. Core attention is given to mapping energy-system problems into quantum-compatible formulations, e.g., Quadratic Unconstrained Binary Optimization (QUBO) and Ising models, and to the associated challenges of discretization, constraint handling, embedding, and scalability. Quantum computing shows the strongest alignment with combinatorial discrete problems, including decomposed unit commitment, network reconfiguration, contingency screening, and selected planning decisions. Problems involving continuous variables, nonlinear physics, or dense constraints, such as full Alternating Current Optimal Power Flow (AC-OPF) or integrated planning-operation models, remain poorly suited to current quantum hardware and formulations.

Most reviewed applications are proof-of-concept, tested on simplified or reduced-size systems. No convincing evidence of practical quantum advantage for realistic large-scale energy-system problems currently exists. Hybrid quantum-classical architectures represent the most credible near-term pathway, quantum solvers handle discrete combinatorial subproblems, while classical methods maintain full system feasibility and operational validity.

Critical research gaps include the absence of realistic benchmarking, inefficient problem encodings, limited large-scale validation, and insufficient treatment of uncertainty, markets, and system-level constraints. Future work should prioritize hybrid solution architectures, efficient problem mappings, standardized benchmarks, and pilot applications embedded within operational workflows.

Quantum computing should be treated as a specialized computational accelerator for selected problem classes, not a replacement for classical optimization. Practical adoption requires continued advances in algorithms, hardware fidelity, benchmarking standards, and integration into real energy-system environments.

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List of Abbreviations

AC	Alternating Current
AC-OPF	Alternating Current Optimal Power Flow
ADMM	Alternating Direction Method of Multipliers
DC	Direct Current
DC-OPF	Direct Current Optimal Power Flow
DER	Distributed Energy Resources
EDF	Électricité de France
EMERGE	Internal TNO hybrid power plant energy management system modelling
HHL	Harrow–Hassidim–Lloyd Algorithm
HPC	High-Performance Computing
LP	Linear Programming
MILP	Mixed-Integer Linear Programming
MIP	Mixed-Integer Programming
NISQ	Noisy Intermediate-Scale Quantum
NP-hard	Non-deterministic Polynomial-time hard
OPF	Optimal Power Flow
QAE	Quantum Amplitude Estimation
QAOA	Quantum Approximate Optimization Algorithm
QC	Quantum Computing
QML	Quantum Machine Learning
QUBO	Quadratic Unconstrained Binary Optimization
SCUC	Security-Constrained Unit Commitment
TSO	Transmission System Operator
TULIPA	Open-source energy-system optimization framework
UC	Unit Commitment

1 Introduction and Scope Definition

The purpose of this chapter is to define the motivation, scope, and methodological boundaries of this literature review. It establishes why quantum computing has attracted attention in the context of energy systems, clarifies which problems and approaches are considered relevant, and explicitly describes what is outside the scope of this work. This boundary-setting is essential to prevent scope creep and to ensure a focused, application-driven review.

1.1 Motivation: Computational Bottlenecks in Energy Systems

Modern energy systems, particularly electric power systems, are undergoing a rapid increase in scale, complexity, and operational uncertainty. High penetration of renewable energy sources, increasing decentralization, sector coupling, and the proliferation of real-time data streams have significantly intensified computational demands on planning and operational tools. Core system-level tasks such as optimal power flow (OPF), unit commitment, economic dispatch, grid expansion planning, and real-time market clearing are characterized by large-scale, nonlinear, stochastic, and often combinatorial optimization structures.

Many of these problems are known to be NP-hard (Non-deterministic Polynomial-time hard, i.e., computationally very difficult to solve) or exhibit exponential scaling with system size. As a result, even state-of-the-art classical solvers and high-performance computing infrastructures encounter practical limitations when addressing realistic, high-fidelity models. For example, large-scale AC optimal power flow problems with detailed network representations, security constraints, and uncertainty modeling can approach or exceed feasible computation times for operational decision-making [1]. Similar bottlenecks arise in stochastic and robust formulations, where the number of scenarios grows rapidly with renewable uncertainty and system complexity. These computational challenges are widely documented in the literature. Recent review studies explicitly highlight the ever-increasing computational burden associated with maintaining reliable and economically efficient grid operation under modern conditions, particularly as systems transition toward renewable-dominated and low-inertia regimes [2]. While classical decomposition, approximation, and heuristic techniques partially mitigate these challenges, they often do so at the expense of solution optimality, scalability, or transparency. This persistent gap between problem complexity and available computational capability forms the primary motivation for exploring alternative computational paradigms.

1.2 Why Quantum Computing Is Being Considered

Quantum computing has emerged as a potential complementary approach to address selected computational bottlenecks in energy systems. By exploiting quantum-mechanical phenomena such as superposition and entanglement, quantum computers can explore large combinatorial search spaces in ways that differ fundamentally from classical architectures. This property has motivated research into quantum algorithms for optimization, sampling, and simulation tasks that are central to energy system analysis.

Several core energy system problems map naturally to combinatorial optimization structures, including binary decision variables in unit commitment, network reconfiguration, contingency analysis, and expansion planning. Quantum optimization techniques, such as quantum annealing and variational algorithms including the Quantum Approximate Optimization Algorithm (QAOA), have therefore been proposed as potential accelerators for these discrete subproblems [3].

Early proof-of-concept studies have demonstrated the feasibility of encoding simplified power system problems into quantum-compatible formulations and executing them on existing quantum hardware. Notable examples include experimental demonstrations of DC power flow and network optimization on quantum annealers [4], as well as hybrid quantum-classical formulations of unit commitment and stochastic dispatch problems [5]. While these studies remain limited in scale and do not yet demonstrate a clear computational advantage over advanced classical methods, they provide important evidence that quantum approaches can be meaningfully integrated into energy system workflows.

Importantly, the prevailing consensus in the literature is that quantum computing is not expected to replace classical computing for energy systems in the foreseeable future. Instead, most realistic approaches adopt a hybrid quantum-classical paradigm, in which quantum processors address the most computationally challenging combinatorial components, while classical solvers retain responsibility for continuous optimization, simulation, and system integration [6]. Within this framing, quantum computing is viewed as a specialized computational accelerator rather than a general-purpose alternative.

Industry interest further reinforces this perspective. Grid operators, utilities, and energy companies have initiated exploratory pilot projects to assess whether quantum methods could enhance contingency analysis, network reconfiguration, and planning under uncertainty. Examples include collaborations involving E.ON (a major privately-owned European energy company) and IBM on energy optimization workflows, pilot studies by EDF (Électricité de France) exploring quantum approaches for grid and energy management applications, and initiatives involving Toshiba and European energy stakeholders on combinatorial optimization for power-system operations [2, 6, 7]. Such initiatives demonstrate that quantum computing is being evaluated not only as a theoretical concept, but as a potential future tool within operational energy system contexts.

1.3 Scope, Assumptions, and Exclusions

This literature review focuses on the intersection of energy system modeling, optimization, and quantum computing, with particular emphasis on computationally challenging problems in electric power systems. The scope is deliberately restricted to system-level applications, including transmission and distribution grids, electricity markets, and integrated energy system planning and operation, where computational complexity is a dominant concern. The overall objective of this review is to critically assess the realistic potential of quantum computing for these applications, identify which classes of problems are structurally compatible with current and near-term quantum approaches, evaluate the main technical and formulation-related limitations, and examine where hybrid quantum-classical methods may provide practical value within future energy system workflows.

Several exclusions are made explicit. This review does not cover quantum chemistry, material science, or device-level applications of quantum computing related to energy technologies, such as battery materials or photovoltaic materials. It also excludes quantum communication, quantum cryptography, and quantum sensing applications, as these fall outside the computa-

tional focus of this work. Furthermore, this review does not aim to provide a tutorial on quantum hardware design, quantum error correction, or low-level quantum programming.

The review assumes that the reader has a working knowledge of classical energy system optimization and simulation techniques, such as linear programming, and mixed-integer programming. Quantum computing is treated as an abstract computational resource rather than a physical system, and only algorithmic concepts necessary to understand energy applications are discussed.

A key assumption underlying this review is the practical relevance of near-term quantum computing. The focus is therefore on approaches compatible with Noisy Intermediate-Scale Quantum (NISQ) devices and hybrid quantum-classical workflows. Fully fault-tolerant, large-scale quantum computing is considered only insofar as it provides context for long-term potential, not as a basis for near-term application claims.

1.4 Methodology for Literature Selection

A structured and transparent methodology was adopted to identify and select relevant literature. Primary sources were collected from major scientific databases and digital libraries, including IEEE Xplore, Scopus, ACM Digital Library, arXiv, and Google Scholar. Search queries combined energy system keywords (e.g., power systems, energy markets, optimization, grid planning) with quantum-related terms (e.g., quantum computing, quantum optimization, quantum annealing, QAOA).

The initial search focused on publications from approximately 2018 to 2025, reflecting the rapid evolution of the field. Inclusion criteria emphasized relevance to energy system applications, technical rigor, and clarity of problem formulation. Preference was given to peer-reviewed journal articles, peer-reviewed conference proceedings, and review papers that provided either broad overviews of the field or substantial methodological contributions. Particular emphasis was placed on studies presenting explicit problem formulations, implementation details, benchmarking results, or experimentally validated case studies relevant to energy-system applications [2]. Selected industry reports and pilot studies were included where they provided substantive technical insight into real-world feasibility.

In addition to broad review and survey papers, targeted efforts were made to include recent methodological and application-oriented studies relevant to practical energy-system use cases. Particular attention was given to work addressing power-network optimization, unit commitment, distributed energy management, tactical capacity management, and energy storage scheduling using quantum optimization techniques. This includes studies on QUBO-based formulations, quantum annealing approaches, and hybrid quantum-classical methods for operational and planning problems in power systems [8, 9, 10, 11, 12, 13].

Exclusion criteria were applied to remove sources addressing quantum computing in a purely theoretical context without connection to energy systems, or energy studies that referenced quantum computing only superficially. Redundant publications were consolidated, and non-technical opinion pieces were excluded. Given the rapid evolution of the field and the prevalence of preprints, some included studies may not yet reflect long-term methodological consensus.

After the initial selection, additional key references were identified by reviewing citations in foundational papers. The final set of sources includes academic reviews, methodological studies, experimental demonstrations, and selected industry case studies. Together, these references provide a balanced and critical view of the current state of quantum computing applications in

energy systems.

1.5 Research Questions

This review is guided by the following research questions:

1. Which classes of energy system problems are structurally compatible with quantum computing?
2. What realistic advantages can quantum computing provide under current limitations?
3. What are the dominant technical and formulation-related bottlenecks?
4. Which hybrid quantum–classical approaches appear most promising?
5. What is the realistic pathway toward practical adoption in energy systems?

2 Energy System Problems of Interest

2.1 Characteristics of Modern Energy Systems

Modern *electricity* systems face several challenging characteristics that lead to complex decision-making and optimization problems. Specifically, these systems are *large-scale and interconnected*, such as those at the European level. They are influenced by *stochastic* renewable energy operations, which depend on weather conditions for availability. Additionally, many dispatchable generation decisions are *non-convex*, such as on/off decisions for thermal power plants. Lastly, these systems involve *multi-timescale dynamics*, where the lifetime of investment decisions spans several years. Below, we highlight each characteristic with real-world examples, with particular focus on the Netherlands and Europe.

2.1.1 Large-Scale and Interconnected Systems

Contemporary power systems are vast in scope, comprising thousands of generators, loads, and network nodes. National grids are interconnected into continental-scale networks (e.g., the European grid links dozens of countries), yielding a highly meshed system with massive power exchanges [14]. Managing such a scale leads to decision problems with extremely high spatial dimensionality. For example, an optimization model for the European electricity market or grid expansion can contain on the order of millions of variables and constraints [15]. As an example, the Dutch power system is tightly integrated into the pan-European network, with electricity traded across borders (e.g., with Germany and Belgium), so any operational planning must account for cross-border flows and constraints [16]. The size of these systems necessitates computational tools capable of handling very large problem instances.

2.1.2 Stochastic and Variable Supply/Demand

The increasing share of renewable energy sources (wind, solar) has introduced significant *variability and uncertainty* into energy systems. Supply from wind turbines and solar panels is weather-dependent and fluctuates on hourly and daily timescales, while electricity demand also varies and is uncertain in forecasts. Modern power systems are therefore *stochastic* in nature: many inputs to decision problems (loads, renewable generation) are not known precisely in advance. For instance, the Netherlands has experienced hours of excess solar generation, leading to negative power prices, followed by sudden shortfalls that require fast-ramping gas plants; operators must plan for a range of outcomes [17] and [18]. This stochasticity necessitates probabilistic approaches or safety margins in operations to maintain reliability. In practice, system operators use techniques such as day-ahead forecasts with reserved balancing power to hedge against uncertainty, or incorporate scenario analyses to represent different possible futures. The key point is that *uncertainty is inherent* and cannot be ignored: robust plans must ensure system security across a spectrum of conditions [19].

2.1.3 Non-Convexities and Discreteness

Many core decision problems in energy systems involve *non-convex* relationships and binary or integer decisions. A prominent example is the *unit commitment* problem of scheduling the on/off states of power plants. Because commitment decisions are binary (0/1) and there are minimum output levels, startup costs, etc., the optimization becomes a mixed-integer program (MIP). The unit commitment problem is known to be NP-hard [20], meaning that computational difficulty grows exponentially with problem size in the worst case. Similarly, the physics of electricity flow in AC networks is governed by non-linear equations (power flow equations). The *AC optimal power flow (AC-OPF)* problem, which seeks an optimal dispatch respecting these non-linear constraints, is non-convex and can have multiple local optima. Solving AC-OPF to global optimality is challenging; it has been shown that, in general form, it is NP-hard as well [21]. To manage complexity, system operators often linearize or simplify these constraints (e.g., by using a DC approximation of the power flow that yields a linear model). Non-convexities also arise from network security rules (e.g., N-1 contingency constraints introduce logical conditions) and from market designs (block bids in markets are all-or-nothing). In summary, the decision landscape in energy systems is often rugged and non-convex, necessitating advanced mathematical programming techniques to obtain high-quality solutions.

2.1.4 Multi-Timescale Decisions

Electrical infrastructure and operations involve a hierarchy of *multiple timescales*: from long-term investment planning (looking years or decades ahead) to seasonal and daily scheduling, down to real-time control and millisecond protection responses. These layers are strongly inter-dependent. For example, long-term generation investment decisions (e.g., building new wind farms or gas plants) determine which resources are available for daily operations; conversely, difficulties encountered in daily operations (e.g., frequent congestion or reserve shortages) indicate where new investments or reinforcements are needed.

There is also a multi-timescale aspect within system operation itself. Operators perform day-ahead unit commitment, adjust generation in hourly or 15-minute intra-day markets, and balance supply and demand in real time every few seconds. Each timescale has its own optimization or decision problem, and linking them is complex, see the example in [22]. In the Netherlands, for instance, planners must ensure that capacity expansion plans for 2030 remain robust under hourly variability and short-term emergency conditions. This often requires detailed operational simulations following high-level planning studies to verify feasibility.

The multi-timescale nature of these problems implies that a truly optimal strategy would ideally require joint optimization across all timescales. In practice, however, this is computationally intractable, so approximations are commonly used. A typical approach is sequential planning, where long-term investments are optimized first and system operation is evaluated afterward using the resulting infrastructure [23, 24]. Furthermore, the presence of multiple timescales significantly increases the number of decision stages in optimization models (e.g., 8760 hourly operational steps per year, or multiple representative periods in long-term planning). Handling all of these stages simultaneously within a single model remains extremely challenging.

2.2 Canonical Problem Classes in Energy Systems

In light of the above characteristics, several *canonical classes of decision problems* regularly appear in electricity system analysis. We group them into three broad categories: (i) *Optimization problems* for planning, operations, and market clearing; (ii) *Decision-making under uncertainty*, including stochastic and robust formulations; and (iii) *Network-constrained problems*, where

Table 2.1: Key characteristics of contemporary electricity systems and implications for decision problems.

Characteristic	Description	Implications for Problems
Large-scale (interconnected)	Thousands of network nodes, generators, and loads spanning wide areas; cross-border power flows are common.	Very high-dimensional optimization problems (millions of variables and constraints); data handling becomes non-trivial; decomposition techniques are often required for tractability.
Stochastic (uncertainty)	Significant uncertainty in supply (wind and solar output) and demand; fast fluctuations and forecast errors.	Requires probabilistic, stochastic, or robust decision-making (scenarios, reserves); purely deterministic models risk infeasibility or excessive system costs.
Non-convex (discrete, nonlinear)	Binary decisions (unit commitment, investments) and nonlinear power-flow physics.	Problems are NP-hard or non-convex; global optimality is hard to guarantee; MIP solvers, relaxations, and approximations are standard.
Multi-timescale	Decisions span from long-term planning (years) to real-time operation (seconds), with strong inter-temporal coupling.	Full co-optimization across all horizons is computationally prohibitive; problems are usually decomposed (e.g., planning vs. operation), at the cost of optimality.

power flow constraints are explicitly considered. Each category is illustrated with examples (notably from Dutch/European contexts).

2.2.1 Optimization for Planning, Operations, and Markets

Many fundamental problems are naturally formulated as optimization tasks: typically, minimizing total cost (or maximizing social welfare) subject to operational and physical constraints.

Long-term planning optimization:

These problems determine the optimal mix of future infrastructure investments. For example, *generation expansion planning* asks: which new power plants (and other resources like storage) should be built over the next 10–30 years, and when, to meet growing demand and policy targets at minimum cost? Similarly, *transmission expansion planning* identifies the new transmission lines or upgrades required. Planners must consider capital and fuel costs, as well as the ability to reliably meet demand across various scenarios. Such models often use multi-year horizons with representative time periods for operations, and they can be very large mixed-integer linear programs (MILPs) when discrete choices (e.g., whether to build a project) are included. For instance, a Dutch planning study might optimize investments in offshore wind farms, gas plants, and transmission corridors for the 2035 horizon, minimizing total discounted cost while ensuring adequacy and meeting emissions targets [25].

Short-term operational optimization:

On the operational side, the prototypical problem is the *Unit Commitment (UC) and Economic Dispatch*. Here, the goal is to schedule existing generation units over a short horizon (e.g., 24–48 hours, typically in hourly or sub-hourly intervals) to meet forecasted demand at minimum production cost, while respecting each unit’s technical constraints and system-wide requirements (such as each hour). The dispatch part decides the generation level (continuous power output) for each committed unit. Constraints include generator limits, minimum uptime/downtime, ramp rate limits, and overall demand-supply balance. UC problems are solved daily by system operators and market clearinghouses worldwide, for example, TenneT, the Dutch Transmission System Operator (TSO), for reserve procurement and by market algorithms for the day-ahead

energy market. Because UC is a large MIP (with dozens to thousands of units over 24+ hours), practical solutions use sophisticated solvers and heuristics to obtain high-quality schedules within limited time [20]. Another operational optimization is the *economic dispatch* at shorter intervals (e.g., real-time dispatch every 5 minutes to adjust outputs, often solved as a linear program fixing which units are on). These operational optimizations ensure that the power supply meets demand at minimal cost while adhering to all technical constraints.

Market clearing optimization:

In liberalized electricity markets, market clearing can be viewed as an optimization problem run by an independent market operator. In a day-ahead market, generators submit offers (quantity of MWh at certain prices) and consumers submit bids; the market algorithm then maximizes total social welfare (equivalently, minimizes total cost to serve demand) by selecting which bids/offers clear, subject to demand equaling supply and other market rules. European market coupling is one example: the EUPHEMIA algorithm clears the combined day-ahead market for Europe by identifying the accepted offers from each country and the implied power flows between countries that maximize welfare subject to cross-border transmission limits. This is formulated as a large-scale mixed-integer linear optimization problem, complicated by block bids (which introduce integer constraints) and the coupling of energy with reserve markets [26]. The result yields market prices for each zone and interconnector flows. Market-clearing problems are similar to operational dispatch optimization problems, but must handle the specific bid formats and often simplify the underlying physics (often using zonal models rather than full-network detail). They are typically solved within very short time frames (e.g., 5-15 minutes for a day-ahead market run covering 24 hours and dozens of bidding zones).

In summary, whether for investment planning, unit commitment, or market clearing, formulating and solving an optimization problem is a common approach to derive decision support in energy systems.

2.2.2 Uncertainty and Stochastic Decision-Making

Because of the stochastic nature of energy systems, classical deterministic optimization (which assumes a single forecast for everything) can be inadequate. Two major paradigms exist to incorporate uncertainty:

Stochastic optimization: These models explicitly consider multiple *scenarios* or realizations of uncertain parameters within the optimization. A common approach is two-stage stochastic programming: first-stage decisions (here-and-now, e.g., which generators to commit day-ahead, or which investments to make) are made before uncertainty resolves, and second-stage decisions (recourse, e.g., how to dispatch generation or how much load to shed in each scenario) are made after seeing the outcome of uncertain factors [19] and [27]. The objective minimizes the expected cost over all scenarios (or a risk-adjusted criterion). For example, a stochastic unit commitment model for the Netherlands might include 50 scenarios of wind power availability for the next day, each with a probability; the UC solver then finds a single commitment plan that minimizes expected operating cost across those scenarios (implicitly procuring extra reserves if needed to handle low-wind cases). Such models can significantly improve reliability and cost-effectiveness under uncertainty, compared to deterministic models, by hedging against plausible contingencies. However, they are much larger in size (the number of scenarios multiplies the number of constraints and variables) and hence computationally challenging. Another use of stochastic optimization in energy is for planning under uncertainty (e.g., considering uncertain fuel prices or demand growth paths in investment planning) [28]. In practice, due to computational constraints, pure stochastic optimization with many scenarios is rarely used in industry; instead, a limited number of scenarios or representative days are

included, or stochastic models are employed in research settings to assess the value of stochastic solutions.

Robust optimization and deterministic heuristics: An alternative approach is *robust optimization*, which seeks decisions that perform well under the worst-case realization of uncertainty within some bounds. For instance, a robust unit commitment might ensure feasibility for any wind output within a lower and upper bound, rather than relying on probabilistic estimates. Robust solutions are safe against uncertainty but can be overly conservative and costly. Methods have been developed to soften this (e.g., adaptive robust optimization) and have been applied to unit commitment as well [29]. On the other hand, the most common industry practice remains deterministic optimization combined with *ex-post scenario analysis*. In this approach, one solves a deterministic optimization problem using best-estimate inputs (e.g., forecasted demand and mean wind), then tests or adjusts the solution by simulating a few alternative scenarios. If one of those scenarios reveals a problem (e.g., insufficient reserves if a large plant fails), the plan is manually adjusted (commit additional units or purchase reserves). Essentially, human judgment and simple rules (like “always hold 15 % reserve capacity for forecast error”) augment the deterministic optimization. This approach is easier to implement with existing tools and avoids the exponential growth in model size that stochastic programming entails, at the expense of not guaranteeing optimality under uncertainty. In summary, uncertainty is addressed either by embedding it into bigger optimization models (stochastic/robust methods) or by heuristics and scenario testing outside the optimization. Both strategies acknowledge the importance of uncertainty in modern energy systems, particularly with respect to renewables [17], and thus differ from classical deterministic planning.

2.2.3 Network-Constrained Problems

Electricity systems are networks governed by the laws of physics. Thus, a critical class of problems explicitly models the *power network constraints* to ensure grid feasibility and security.

The canonical problem here is the *Optimal Power Flow (OPF)*. OPF determines the most economical operating point (generator outputs, possibly flexible demands, etc.) that satisfies all electrical network constraints: power flow equations (Kirchhoff’s laws), transmission line capacity limits, voltage magnitude bounds, etc. If we consider the full AC power-flow model, the OPF is a nonlinear, non-convex optimization problem. In practice, a linearized variant known as DC-OPF is often used for simplicity: it assumes fixed voltages and small angle differences, converting the problem to a linear (or quadratic) form. OPF can be solved at a single snapshot (e.g., one hour) to dispatch generation subject to network limits. For example, to manage congestion in the Dutch grid, TenneT might solve a DC-OPF to re-dispatch generation (increasing some plants and decreasing others) so that no transmission line is overloaded and costs are minimized. Network-constrained unit commitment is an even larger problem that combines UC (with binary unit variables) and OPF (linear power-flow constraints), often referred to as security-constrained unit commitment (SCUC) in U.S. terminology. These problems ensure that the solution not only balances supply and demand but also respects the grid bottlenecks and voltage requirements.

Another important network-constrained problem is the *N-1 security analysis* and the optimization of remedial actions. System operators must ensure that the grid can withstand the failure of any single component (a line, generator, or transformer outage). This is enforced by N-1 constraints in optimization problems: for each critical outage scenario, the post-contingency flows, or voltages, must remain within limits (possibly after some automatic or planned corrective action). Including all N-1 conditions (hundreds or thousands of them in a large grid) makes OPF/SCUC problems extremely large. Often, a contingency analysis is done outside the main

Table 2.2: Major classes of energy system problems with examples.

Problem Class	Description (Decision Variables and Constraints)	Example Scenario
Long-term planning optimization	Choose new investments in generation and transmission to meet future demand and policy goals at minimum cost. Typically, a multi-year MILP with binary investment variables and capacity expansion constraints.	Optimize the 2030 Dutch power mix (build offshore wind, gas capacity, and/or interconnectors) to minimize total cost while achieving renewable targets.
Short-term operational optimization	Commit and dispatch available generation units to meet load at least cost over 24–48 h. Mixed-integer problem (unit on/off variables plus generation levels).	Day-ahead scheduling: decide which plants in the Netherlands to turn on and their hourly outputs for tomorrow, minimizing production cost while meeting forecast demand.
Market clearing (economic dispatch)	Allocate generation and consumption based on bids and offers to maximize social welfare (or minimize cost). Often formulated as an LP with supply–demand balance and possibly network constraints.	European day-ahead market coupling: clear bids across countries (NL, DE, etc.) to produce market prices and cross-border flows that respect transmission limits (e.g., Euphemia).
Stochastic/robust optimization	Incorporate uncertainty (multiple scenarios or worst-case realizations) into planning or operation. Often two-stage: first-stage here-and-now decisions, second-stage recourse decisions.	Stochastic unit commitment in a high-wind system: commit units day-ahead considering many wind scenarios, minimizing expected cost while ensuring adequate reserves in all scenarios.
Network-constrained dispatch (OPF)	Optimize dispatch subject to transmission constraints (power-flow equations, line limits, voltage bounds). Nonlinear in AC form; often approximated by DC-OPF for tractability.	Congestion management in the Netherlands: re-dispatch north vs. south generation so a critical line is not overloaded, at minimum adjustment cost (via DC optimal power flow).
Network expansion planning	Select new transmission lines or upgrades (binary decisions) to minimize long-run system cost or meet reliability criteria. Commonly, MILP-based or solved with iterative heuristics.	European grid expansion: decide new lines/cables (e.g., an additional NL–Germany interconnector) to enable renewable integration, trading off investment cost against reduced congestion and generation cost.

optimization: e.g., solve an OPF for the base case, then check flows for each contingency and adjust if any violations appear. This sequential approach is not strictly optimal but is tractable.

On the planning side, *network expansion planning* problems address where to build new lines or transformers to alleviate congestion. These are typically formulated as MILPs (binary decisions to build each candidate line or not, plus continuous power-flow variables). Given the large number of potential expansions in a meshed grid, the problem can become very complex, and heuristics or decomposition (e.g., iterative addition of lines) are used. European grid development plans (such as ENTSO-E’s Ten-Year Network Development Plan [30]) use a combination of expert scenarios and optimization to propose new interconnectors (e.g., new submarine cables from the Netherlands to Norway to exchange renewable energy). Network expansion and OPF problems ensure that the physical feasibility of power delivery is respected in all planning and operational decisions, which is crucial because even an economically optimal plan is useless if it violates network limits.

2.3 Computational Limits of Classical Approaches

The problem classes above are typically addressed using classical algorithms (e.g., linear and mixed-integer programming solvers, decomposition methods, and heuristics). However, as the scale and complexity of energy systems have grown, these traditional techniques face increasing *computational challenges*. In many cases, there is a gap between the problem sizes we want to solve and what current algorithms can reliably handle in practical time. This section discusses key computational limitations encountered with classical methods, supported by examples from Dutch and European system studies.

It should be noted that classical energy-system optimization already relies heavily on model-reduction and aggregation techniques to improve tractability. Examples include representative-day selection, zonal aggregation, reduced network representations, DC approximations of AC power flow, decomposition methods, and surrogate models. These approaches reduce the dimensionality and sparsity structure of optimization problems while attempting to preserve the dominant system behavior. In practice, many large-scale planning and operational studies would be computationally infeasible without such simplifications. However, these reductions also introduce trade-offs between computational efficiency, physical accuracy, and temporal or spatial fidelity.

2.3.1 Scalability Challenges in Large-Scale Optimization

Even deterministic optimization models (no stochastic scenarios) become extremely large for realistic systems. The number of variables and constraints grows with the number of assets (generators, loads, lines), the number of time steps, and the level of detail of the technical constraints modeled. For example, a unit commitment or economic dispatch over a full year at hourly resolution has $24 \times 365 = 8760$ time steps. If there are 100 generators with on/off and dispatch variables, that is on the order of $8760 \times 100 \approx 876,000$ decision variables just for generation levels, plus another 876,000 binary on/off decisions, ignoring network flows. Adding network flow variables per line and other constraints easily raises the problem size to the millions. In an integrated European model with thousands of generators and nodes, one can end up with tens of millions of variables/constraints [15]. Solving such huge linear programs or MILPs pushes current solvers to their limits in terms of memory and computation time. One approach is to reduce time resolution or scale: e.g., instead of hourly steps for 8760 hours, use representative days or weeks (e.g., 100 representative time slices) to shrink the problem [23, 24]. This is commonly done in European capacity expansion models to remain tractable. Another approach is to decompose the problem spatially or hierarchically: solve separate optimization problems for different regions or time segments, then coordinate them. For instance, the European market coupling problem is decomposed into a coordinated but distributed solution for each market zone, rather than a single monolithic optimization, due to computational time constraints. In summary, current MILP/LP solvers can handle large problems but struggle as we push into the multi-million-variable range, often necessitating model-reduction techniques [31]. The *curse of dimensionality* is very present: adding more detail (more units, finer time steps, more constraints) can make a previously solvable problem unsolvable within practical time.

2.3.2 Combinatorial Explosion with Uncertainty

Incorporating uncertainty via scenarios significantly exacerbates the scale issue. A stochastic optimization with N scenarios can be thought of as N copies of the deterministic problem (one for each scenario's second-stage), connected by first-stage decisions. If a deterministic UC has, say, 200k variables, a stochastic UC with 100 scenarios might have on the order of 20

million variables (minus some coupling structure that solvers can exploit). Even with modern computing, solving a 20-million-variable MILP remains an immense task. In practice, this limits stochastic formulations to a relatively small number of scenarios (perhaps a handful up to a few dozen), which may not fully capture the tail risks or the full distribution of uncertainties [19]. An example: a research study might formulate a stochastic unit commitment for the Dutch system with 10 wind scenarios. That may already push a solver to run for several hours. Trying 100 scenarios may yield no solution within a reasonable time (days). As a result, system operators usually handle uncertainty through simpler means (like deterministic plus reserve margin, or separate Monte Carlo simulation outside the optimization loop). Monte Carlo simulation itself (running a deterministic optimization hundreds of times for random samples) can be very computationally intensive, though it is embarrassingly parallel (runs can be done concurrently). The computational explosion is not only in time but also in memory: storing a huge scenario tree or the full model in memory can exceed RAM limits. Techniques such as scenario reduction (choosing a small representative subset of scenarios) [23, 24] and Benders decomposition (solving the scenario subproblems separately and iterating) are used to cope with this, but they add complexity to the modeling process. In short, handling uncertainty optimally is often computationally prohibitive for large systems with classical methods, forcing practitioners to trade solution optimality for tractability.

2.3.3 Difficulty with Integer Decisions and Heuristics

Mixed-integer problems (like unit commitment, expansion planning) suffer from combinatorial growth in possibilities. Branch-and-bound (or cutting-plane) algorithms in MIP solvers can, in the worst case, enumerate an astronomical number of node subproblems. While solvers have improved by orders of magnitude in the last few decades, there are still limits. For instance, the European day-ahead market clearing (Euphemia) includes integer constraints on block bids and must find a solution within minutes; it cannot perform an exhaustive search, so it relies on heuristic rules and priority orders to prune the search space. Similarly, in operations, if a MIP solver cannot prove optimality in the allotted time (say 1 hour for a day-ahead UC), it will return the best solution found so far. There have been cases in which system operators run out of time and must manually adjust the schedule or use a suboptimal solution because the MIP did not converge. To cope, many practical approaches use *heuristics* or simplified models. A common heuristic for UC is priority listing: commit the cheapest units first until demand is met, subject to feasibility constraints. This was used historically before MIP solvers were common and yields a feasible, if not optimal, solution quickly. Modern implementations might use hybrid approaches: run a relaxed LP to obtain an estimate of generation levels, then use rounding or custom logic to determine integer values, and finally polish with the MIP solver. While these often work well, they can result in slightly higher costs or, in some edge cases, infeasibility that requires manual correction. In expansion planning, heuristics such as iteratively adding the line with the highest benefit are used instead of solving the full combinatorial MILP, which may miss the truly optimal combination of lines but is far easier to compute. In summary, classical solvers sometimes require assistance to handle combinatorial complexity: either by providing a good starting point (heuristics) or by simplifying the problem (fewer integer variables). This limitation is intrinsic to NP-hard problems, unless $P = NP$, we cannot expect an exact polynomial-time algorithm to always solve them, nor can a quantum computer with current state-of-the-art capabilities. Thus, in real systems, one often accepts slightly suboptimal but timely solutions over optimal but intractable solutions.

2.3.4 Non-Convex Power Flow and Decomposition

As mentioned, the AC power flow equations make OPF problems non-convex. Current practice for handling AC-OPF is to run iterative nonlinear solvers (e.g., Newton-Raphson-based OPF),

which are not guaranteed to find a feasible solution. There is also no guarantee of global optimality, and, in fact, the result may be a local optimum or merely a feasible point that engineers deem "good enough." In many cases, slight suboptimality is an acceptable trade-off for tractability in power flow problems. Additionally, including N-1 security and other network constraints in MIPs (e.g., SCUC with N-1) can lead to extremely large formulations that are practically unsolvable. Thus, operators decompose problems: for example, ERCOT (Texas) might solve a day-ahead SCUC without all N-1 constraints, then separately check security and adjust with a second OPF; European TSOs do a market solve assuming no internal network limits, then manage internal congestion afterwards through redispatch. These decomposition approaches break what is, in principle, a single large optimization problem into manageable pieces that are solved sequentially. The downside is that the overall solution may not be globally optimal or coordinated. For instance, the market might commit generators that the TSO later needs to curtail due to network limits that were not considered in the market-clearing stage, leading to out-of-market adjustments and potentially higher costs than an integrated solution. However, a fully integrated market + network + security optimization would be enormous and intractable with current methods.

Another aspect is that to avoid AC complexity, linear DC-OPF is used in most markets. This ignores losses and voltage issues, which can be handled in later refinements. AC feasibilities are then checked afterwards. Researchers have developed convex relaxation techniques (using semidefinite programming or other methods) to solve OPF globally [21], but these are not yet standard in industry, partly due to computational overhead and implementation complexity. The net effect is that classical methods deal with non-convex structures by either *relaxing* them (solving an easier convex problem and then adjusting the result to be feasible) or by *fixing parts of the problem* (e.g., commit first, then dispatch, rather than jointly optimizing). Each of these introduces a suboptimality gap or requires further iteration.

2.3.5 Limits of Hardware and Solution Time

A practical limitation is the availability of computing resources and time. Even if a very large problem can be solved given enough memory and time, there are deadlines in real operations (markets must clear by a certain time each day; operators need results quickly to act on them). For example, the day-ahead market clearing starts at noon and must finish by around 12:40 to publish results for the next day; this 40-minute window includes collecting bids, running the optimization, and validating results. This effectively caps the algorithm's complexity. Likewise, a TSO running contingency analysis every 15 minutes cannot afford a 1-hour optimization in that loop. In planning studies, one might have more time, but the analysis often requires running many cases (for sensitivities, scenario analyses, etc.), so each individual run still needs to be reasonably fast.

While high-performance computing (HPC) can be used to solve larger models (e.g., by parallelizing scenario runs and using more cores for the solver), not all analysts have access to it, and even more restricted at the moment, quantum computers. Moreover, certain algorithms do not parallelize well beyond a point (MIP branch-and-bound is somewhat serial in nature, though parallel strategies exist). In research contexts, it is not unusual for a complex stochastic unit commitment or expansion planning run to take hours to days on an HPC cluster [32]. Industry planners, however, often prefer simpler models that run in minutes to at most a couple of hours, for agility and because they might need to run hundreds of variants. For example, an EU-wide energy model might reduce the temporal resolution to obtain a solution in 2 hours rather than 2 days, enabling many scenario runs to be performed in a week's time for a policy study [23]. There is always a trade-off between model fidelity and computational manageability.

Importantly, many practical energy-system optimization problems can already be solved sufficiently well using advanced classical solvers, decomposition techniques, and high-performance computing infrastructures. In many operational settings, approximate or near-optimal solutions obtained within strict time limits are more valuable than exact global optima obtained too late. As a result, current industrial workflows are generally effective for a large range of planning and operational tasks.

The motivation for exploring quantum computing therefore lies primarily in particularly challenging classes of problems, such as very large combinatorial optimizations, scenario-intensive stochastic formulations, and highly coupled multi-timescale problems, where classical computational effort scales unfavorably. In these cases, quantum methods are being investigated as potential accelerators for specific computational bottlenecks rather than as universal replacements for classical optimization.

2.3.6 Summary of challenges

To summarize this section, classical computational approaches (LP/MIP solvers, conventional simulation) are being pushed to their limits by:

- The large scale (spatial detail, many assets) of models needed for modern systems.
- The high resolution (temporal detail, many periods or scenarios) required to capture variability and uncertainty.
- The presence of discrete decisions and non-convex physics, which make problems fundamentally hard.
- The need for (near) real-time solution in operational contexts.

Various workarounds (model reductions, decompositions, heuristics) are employed to cope, but they often introduce a loss of optimality or accuracy. This reality motivates the exploration of advanced solution methods, including those that leverage novel computing paradigms, such as quantum computing. Indeed, there is growing research interest in whether quantum algorithms could one day alleviate some of these computational bottlenecks [33, 7]. For instance, quantum annealing has been tested on small unit commitment problems, and the Quantum Approximate Optimization Algorithm (QAOA) has been proposed to handle binary decision variables more efficiently by exploiting quantum parallelism [13]. While current quantum hardware is too limited to solve full-scale power system problems, initial results show promise for certain classes of optimization and could foreseeably handle larger instances as the technology matures. The potential of quantum computing to revolutionize power system optimization is a key motivation for research at institutions such as TNO.

3 Fundamentals of Quantum Computing (Targeted)

Quantum computing is an emerging computing paradigm that uses quantum mechanics to represent and process information. Different schemes have been proposed to harness quantum mechanical effects in a way that accelerates computation. This section discusses the basic principles of quantum computing, as well as two types of quantum processing units.

3.1 Quantum information basics

Quantum computers operate over quantum data, which is given by the state of a quantum system. A quantum state is typically denoted by $|\psi\rangle$.¹ The basic unit of quantum information is the *qubit*. A single qubit state can be expressed in terms of an orthonormal basis, often denoted $|0\rangle$ and $|1\rangle$. Contrary to classical bits, qubits can be in a *superposition* of the $|0\rangle$ and $|1\rangle$ states,

$$|\psi\rangle = \alpha |0\rangle + \beta |1\rangle$$

with $\alpha, \beta \in \mathbb{C}$ and $|\alpha|^2 + |\beta|^2 = 1$. Upon measurement of this quantum state, the system will collapse into one of the basis states: it will be $|0\rangle$ with probability $|\alpha|^2$ and $|1\rangle$ with probability $|\beta|^2$. This is another key difference with respect to classical data. Quantum states cannot be directly observed, as the observation itself changes the state. Instead, one can prepare the same state multiple times and collect information about $|\alpha|^2$ and $|\beta|^2$ statistically through repeated measurements.

Another differentiating property of quantum systems compared to their classical counterparts is *entanglement*. When two or more qubits are in an entangled state, their individual state cannot be described independently of the state of the others. If a measurement is done on one of the qubits, the state of the remaining qubits changes accordingly. An example of an entangled two-qubit state is

$$|\psi\rangle = \frac{1}{\sqrt{2}} (|00\rangle + |11\rangle) .$$

Quantum computers make use of quantum mechanical effects, such as superposition and entanglement explained above, to perform computations in a fundamentally different way from classical computers.

3.2 Quantum computational models

3.2.1 Digital Quantum Computing

The most well-studied model for quantum computation is the so-called gate-based model, where an initial quantum state is altered using time-discrete operations called quantum logical gates, often simply called *gates* [34]. Gates can be represented as unitary matrices² acting on

¹This is the standard ket notation for quantum states.

²An invertible matrix is unitary if its inverse is equal to its conjugate transpose.

the vector representation of a quantum state

$$|\psi\rangle = \begin{pmatrix} \alpha \\ \beta \end{pmatrix}.$$

They can act on one or more qubits at the same time.

Some subsets of gates are *universal*, meaning that they can be used to construct any arbitrary unitary gate [35]. Quantum computers that natively implement a universal set of gates are called universal. A universal quantum gate set can be used to implement a universal classical gate set [36]. This means that, in principle, any classical computation can be executed in a quantum computer. However, this does not mean that the execution is equally efficient. Quantum computers have been proven to provide computational benefits for specific algorithms [34], yet could be significantly worse at executing others.

3.2.2 Analog quantum computing

Analog quantum computing is a paradigm in which computation is performed by controlling and observing the continuous-time evolution of a quantum system whose natural dynamics encode a problem of interest. Instead of executing discrete quantum gates, an analog quantum computer maps a problem onto a Hamiltonian and allows the system to evolve so that its final state reveals the solution. Analog quantum computers are not universal, yet they are of great interest since they can model systems of computational relevance. Specialization also allows these systems to be less complex and therefore better developed, and more noise resistant [37].

Boson sampling is a specialized model of quantum computation that exploits the interference of indistinguishable bosons (most commonly photons) propagating through a linear optical network. In a typical boson-sampling experiment, single photons are injected into an interferometer composed of beam splitters and phase shifters, and the task is to sample from the resulting probability distribution of photon detections at the output. Sampling from this distribution is strongly believed to be infeasible for classical computers but naturally implemented by quantum optics [38]. Accelerating this computation is expected to have applications in Monte Carlo integration [39, 40] and dense-subgraph sampling [41].

Quantum annealing also falls under the category of analog quantum computing. Here, the computation starts by preparing a state that is the ground state of a simple, well-known Hamiltonian H_I . This Hamiltonian is evolved slowly into a Hamiltonian H_P whose ground state corresponds to the solution to the problem we want to solve. The time-dependent Hamiltonian of the system then reads

$$H(t) = A(t)H_I + B(t)H_P$$

where $A(t)$ and $B(t)$ are decreasing and increasing functions, respectively, and are known as the annealing schedule. If the evolution is sufficiently slow, the end state is the ground state of H_P with high probability. However, the evolution speed required to ensure this condition is impractical. In practice, the system evolves more rapidly, making the method heuristic in nature and thus preventing any guarantee of optimality.

Because of the specialized nature of these devices, it is not possible to implement every Hamiltonian. A common Hamiltonian is the one given by the Lenz-Ising model, whose equivalent mathematical description is a Quadratic Unconstrained Binary Optimization (QUBO) problem, defined as

$$\text{minimize}_{x \in \{0,1\}^n} x^T Q x.$$

where $Q \in \mathbb{R}^{n \times n}$ is a cost matrix. Any problem that can be written in this form can be solved with a quantum annealer.

3.3 Noise, Decoherence, and NISQ Constraints

The physical implementation of these theoretical quantum computational models faces many challenges. Any interaction with a quantum state results in a change in said state. For these reasons, quantum computers are especially susceptible to noise, in particular *decoherence*, a phenomenon through which entanglement degrades and eventually classical behavior emerges. This means that we want to build qubits that are perfectly isolated from their environment, yet at the same time are able to interact with each other and be controlled on demand. That poses a large challenge. It is also complex to scale up these systems while maintaining the possibility of interaction between different components. Operations on the qubits must also happen fast enough to achieve a favorable comparison to classical computers.

A common pitfall when analyzing gate-based quantum algorithms is to ignore the so-called feature mapping step. Data is stored in classical form (bits) and will likely remain so since quantum data decoheres rapidly and is not meant for long-term storage. This means that, to run a quantum algorithm, we must first map our data into quantum form. There are several strategies to do so (e.g., amplitude encoding, rotation encoding), yet preparing such a quantum state can be costly and negate any quantum speed-up. In particular, preparing arbitrary quantum states requires exponentially many gates in the worst case, unless the data has special structure. The limited qubit counts of current hardware can also mean that not all data can be loaded.

Current quantum hardware is at a stage known as Noisy Intermediate-Scale Quantum (NISQ) [42]. Here, intermediate-scale refers to the number of qubits that can be realized within a quantum chip, and noisy refers to the limited control that can be exerted over them. Other than the different computing models described in the previous sections, there are also different physical realizations of qubits, such as superconducting, photonic, trapped ions, or neutral atoms [43]. Each platform comes with different operability trade-offs and is being actively developed by academic institutions and companies alike.

One challenge of particular interest for this report is that of mapping variables to qubits. Talking now specifically about quantum annealers, current hardware does not implement interactions between all pairs of qubits. This means that, for a chip with n qubits, not all matrices $Q \in \mathbb{R}^n$ can be encoded. Mapping a QUBO problem to a physical chip is a process known as *minor embedding* [44]. During this process, a single QUBO variable is likely to be mapped to multiple qubits. For this reason, in practice there is no one-to-one relationship between QUBO size and the number of qubits needed. Sparser matrices need fewer qubits and are therefore preferred.

4 Quantum Algorithms Relevant to Energy Systems

This chapter reviews the main families of quantum algorithms that are potentially relevant to energy system applications, with a particular focus on what is realistically achievable in the near term (the Noisy Intermediate-Scale Quantum (NISQ) era) [42]. The NISQ era refers to the current stage of quantum hardware characterized by intermediate numbers of noisy physical qubits without full error correction, limiting circuit depth and algorithmic scalability [42]. The discussion centers on four categories, described in the following.

4.1 Algorithm Families and Applicability

Quantum approaches proposed for energy systems generally fall into four broad groups:

- **Optimization-oriented algorithms** targeting discrete and mixed-integer problems (e.g., unit commitment, switching decisions, expansion planning).
- **Linear algebra and simulation algorithms** for structured linear systems and accelerated analytical subroutines.
- **Sampling and probabilistic algorithms** aimed at uncertainty quantification, risk assessment, and scenario-based decision-making.
- **Hybrid quantum-classical workflows**, where quantum routines are embedded within classical pipelines for decomposition and evaluation.

A central engineering challenge across all categories is *problem mapping*: translating an energy system problem into a quantum-compatible formulation, such as QUBO/Ising models for annealing or parameterized cost functions for variational circuits, while carefully managing the overhead introduced by discretization, embedding, and constraint handling [2, 7]. This will be the subject of Section 5.

4.2 Optimization-Oriented Algorithms

Optimization remains the most prominent near-term application of quantum computing in energy systems. Many operational and planning tasks involve binary choices (e.g., on/off, build/no-build, switch open/close) that are NP-hard in general. As a result, most current energy-related quantum research concentrates on optimization rather than full-scale quantum simulation.

4.2.1 Quantum Approximate Optimization Algorithm (QAOA)

QAOA is a hybrid variational algorithm designed for combinatorial optimization [45, 46]. It constructs a parameterized quantum state using alternating operators: a problem Hamiltonian encoding the objective (and possibly constraint penalties), and a mixing operator that explores the solution space. A classical optimizer tunes the parameters to minimize the expected objective value obtained from quantum measurements.

QAOA is attractive in the NISQ context because it is hybrid and can operate at moderate circuit depths. However, performance is sensitive to noise, circuit depth, and the effectiveness of classical parameter optimization. Further, an extensive body of work points at a crucial limitation of the family of variational algorithms, of which QAOA is part, namely barren-plateaus [47, 48, 49, 50]. While various mitigation strategies have been proposed [51], some make the resulting circuits classically simulable [52], and no experimental evidence has yet shown QAOA to provide a meaningful computational improvement at scale. Crucially, a large part of the optimization still happens classically, and training variational quantum models has been shown to be NP-hard on its own [53]. For realistically constrained energy problems, QAOA is most credible as a *subroutine* within a larger classical decomposition framework, where feasibility checks and continuous physics (e.g., OPF evaluations) remain classical [6, 7].

4.2.2 Quantum Annealing

Quantum annealing is an analog optimization paradigm tailored to Ising or QUBO formulations [37]. The cost function is encoded into an energy landscape, and the hardware searches heuristically for low-energy states through an annealing process. Unlike classical MILP solvers, annealing does not provide deterministic optimality guarantees.

A key practical constraint is *minor embedding*. Because current annealers have sparse connectivity, dense QUBOs require mapping logical variables onto multiple physical qubits, increasing qubit demand and noise sensitivity [44]. This problem is NP-hard on its own, and is typically solved via heuristic methods [54]. From a modeling perspective, sparsity and constraint-handling strategies are critical in determining whether annealing is viable for a given energy application (see Section 5).

4.2.3 Boson Sampling

Boson sampling has been proposed as a tool for identifying cliques in graphs by encoding the adjacency structure of a graph into a linear-optical network whose output photon-counting statistics preferentially amplify subgraphs with high connectivity [41, 55]. From a complexity-theoretic perspective, simulating the relevant output distributions of boson sampling is widely believed to be classically intractable, suggesting a potential advantage for certain graph instances. However, this advantage is instance-dependent and does not constitute a proven polynomial-time algorithm for the NP-hard maximum clique problem. Additionally, practical scalability is constrained by photon loss, limited controllability of optical networks, and the exponential growth of experimental resources with graph size.

4.3 Linear Algebra and Simulation Algorithms

Linear algebra underpins many power system computations, including sensitivity analysis and state estimation. While quantum linear-system solvers are sometimes cited as promising, their

practical value in energy applications remains limited in the NISQ era.

4.3.1 HHL and Variants

The Harrow–Hassidim–Lloyd (HHL) algorithm solves linear systems of equations by preparing a *quantum state* proportional to the solution vector [56]. Under a number of assumptions (e.g. matrix sparsity, efficient state preparation, oracle access to matrix elements, favorable condition numbers) the algorithm achieves poly-logarithmic scaling in the system dimension, offering an asymptotic improvement over classical direct solvers. As a result, HHL has been widely cited as a foundational primitive for a range of quantum algorithms, including those for solving partial differential equations, accelerating numerical linear algebra, or quantum machine learning.

Despite this theoretical appeal, the applicability of HHL to real-world problems is limited by several restrictive conditions. Many practical applications (particularly in energy systems) require explicit classical representations of solution vectors. Because HHL outputs the solution implicitly as a quantum state, extracting full classical information typically incurs costs that scale linearly with problem size, thereby offsetting the algorithm’s purported quantum advantage. Furthermore, the necessary circuit depths and coherence times are well beyond the reach of current noisy intermediate-scale quantum (NISQ) devices [42]. Consequently, while HHL remains a cornerstone of quantum algorithm theory, its relevance resides in a long-term quantum perspective rather than near-term applications.

4.4 Sampling and Probabilistic Algorithms

Modern energy decision-making increasingly relies on probabilistic analysis, including uncertainty in renewables, risk-aware dispatch, and scenario-based planning. Quantum sampling methods are conceptually appealing in this context, though many require fault-tolerant hardware for a meaningful advantage.

4.4.1 Quantum Amplitude Estimation

Quantum amplitude estimation (QAE) is a fundamental quantum algorithm that can be used to estimate the probability (amplitude) of measuring a specified outcome. It achieves a quadratic speedup over classical Monte Carlo methods by encoding probabilities into quantum amplitudes and extracting them through quantum interference [57, 58]. In practice, however, QAE depends heavily on the ability to efficiently implement the state-preparation operator and its inverse. For many real-world problems, constructing these circuits may be expensive and therefore negate any speed-up. Additionally, QAE requires deep quantum circuits, long coherence times, and many controlled operations. These demands make it poorly suited to NISQ hardware [42].

4.4.2 Quantum Machine Learning

Quantum Machine Learning (QML) is a well-established research field, with mature theoretical foundations and a growing body of experimental and applied work at the intersection of both fields[59]. A widely used perspective in QML, especially in quantum kernel methods and variational quantum classifiers, is that a quantum computer is employed to embed classical data into a high-dimensional Hilbert space via a data-dependent quantum feature map. Data that may be inseparable (or hard to separate) in the original input space can become linearly separable, enabling simple decision boundaries such as hyperplanes to achieve good classification. This

viewpoint closely mirrors the role of kernels in classical machine learning, with the quantum circuit inducing a kernel that may be difficult to compute classically.

In the context of energy systems, QML has been proposed for forecasting (e.g., load, price, renewable output) and classification (e.g., fault detection). While often discussed in surveys, robust empirical evidence of clear advantage in real-world energy forecasting pipelines remains limited and context dependent [2, 7].

4.5 Hybrid Quantum–Classical Algorithms

For energy systems, hybridization³ is widely regarded as the most realistic strategy. In such approaches, quantum routines handle discrete “hard-core” combinatorial structures, while classical solvers manage continuous physics, feasibility checks, and integration [6, 7].

Typical hybrid patterns include:

- **Decomposition-based approaches:** a quantum routine solves a binary master problem, while classical solvers evaluate feasibility and costs.
- **Embedding-based approaches:** a quantum annealer addresses a QUBO subproblem, followed by classical repair and validation.
- **Iterative refinement:** quantum-generated candidates are improved or repaired through classical heuristics.

Most studies agree that, in the near term, quantum computing is more likely to add value through hybrid approaches than through standalone quantum solvers [2, 6, 7].

4.6 Key Takeaways

Most current quantum research in the energy domain focuses on discrete optimization and hybrid quantum-classical approaches. Although linear-algebraic and probabilistic algorithms are theoretically relevant, their practical use for large-scale energy problems is limited by circuit depth, output readout constraints, and hardware noise in the NISQ era [42]. Therefore, broad claims of quantum advantage for full-power system operation and planning are premature given current hardware capabilities.

³Here hybrid refers to horizontally hybrid, as per the taxonomy defined in [60].

5 Mapping Energy Problems to QUBO Formulation

This section presents a brief guide to mapping energy-sector problems onto a formulation suitable for quantum annealing and QAOA. We address how to handle non-binary variables, constraints, and important considerations for mapping the resulting formulation to the actual hardware.

5.1 Decision Variables

The QUBO formulation uses, by definition, binary variables. This poses a challenge for problems that naturally contain some continuous or general integer variables. Several strategies exist to overcome this.

First, let us consider the case of integer variables. Let z denote the integer variable that we want to model, which, without loss of generality, ranges in $[0, u]$ for some $u \in \mathbb{Z}$. The following are some common encoding strategies:

- The one-hot encoding utilizes $u + 1$ binary variables $x_0, \dots, x_u$, where $x_i = 1$ implies $z = i$. The constraint $\sum_{i=1}^u x_i = 1$ needs to be imposed in the model.
- The binary encoding expresses z as a combination of $p = \lceil \log_2(u + 1) \rceil$ binary variables as $z = \sum_{i=0}^{p-1} 2^i x_i$.
- The Gray encoding uses the same number of variables as the binary encoding but ensures only one bit flip when the z 's value changes by one. This can have the benefit of a smoother energy landscape and often, more structured Hamiltonians, compared to the binary encoding. Mathematically, the relationship between the binary encoding variables and the Gray variables is given by $g_{p-1} = x_{p-1}$ and $g_i = x_{i+1} \oplus x_i$ for $i = 0, \dots, p - 2$, where $\oplus$ denotes the XOR operator.
- The domain-wall encoding [61] uses a chain of u variables whose configuration contains exactly one transition (domain wall). This is, variables on one side of the wall take one state and variables on the other side take the opposite state. Valid encodings are imposed via penalties of the form $x_i \cdot x_{i+1}$. The value of the variable is determined by the position of this domain wall along the chain. For example, the value $z = 3$ would be represented as 1110.

Each representation has associated advantages. The binary and Gray encodings result in a more compact formulation (fewer added variables). At the same time, they incur potentially large QUBO coefficients of up to 2^p , which may result in reduced precision. While it uses more variables, the one-hot encoding can offer benefits in modeling certain constraints and in promoting smoothness of the energy landscape. The domain-wall encoding also uses more variables, but enforces validity through efficient local penalties in the form of pairwise couplings.

In the case of continuous variables, a first approach is to discretize them and then apply one of the encodings discussed above. This is discouraged, as it results in considerable inaccuracies and

Classical Constraint	Equivalent Penalty
$x + y \leq 1$	xy
$x + y \geq 1$	$1 - x - y + xy$
$x + y = 1$	$1 - x - y + 2xy$
$x \leq y$	$x - xy$
$x + y + z \leq 1$	$xy + xz + yz$
$x = y$	$x + y - 2xy$
$z = x \wedge y$	$xy - 2xz - 2yz + 3z$

Table 5.1: A selection of known constraint–penalty pairs. Adapted from [63].

a large number of variables. Alternatively, one can resort to decomposition or hybrid methods, where the continuous variables are handled classically, while the binaries are optimized by the quantum hardware. An example of this is the Quadratic Continuous Quantum Optimization method introduced by Mücke et al. [62].

5.2 Constraint Handling Strategies

Many of the optimization problems that arise in practice are, in fact, constrained. This is no different for the problems encountered in the energy sector. Often, these problems can be effectively reformulated into an unconstrained version, in particular a QUBO, by transforming constraints into (quadratic) penalty terms in the objective function. The penalty functions are designed so that they take value zero if and only if the corresponding constraint is satisfied, and they take a value strictly greater than zero otherwise. For a number of common constraints, an equivalent penalty function is known. These are shown in Table 5.1.

More generally, any constraint of the type $\sum_{i=1}^n a_i x_i = b$ can be written as a penalty of the form

$$\left(\sum_{i=1}^n a_i x_i - b \right)^2. \quad (5.1)$$

Other types of constraints may require the use of slack variables. For example, a constraint of type

$$\sum_{i=1}^n a_i x_i \geq b$$

can be transformed into equality form by introducing $p = \lceil \log_2(b+1) \rceil$ binary slack variables, in particular

$$\sum_{i=1}^n a_i x_i + \sum_{j=1}^p 2^{j-1} y_j = b$$

to then be transformed into a penalty, such as in Eq. 5.1.⁴

For each constraint in the problem, an equivalent penalty function $f(x)$ is created and added to the objective function, multiplied by a scalar factor λ that controls the strength of the penalization. For example, for a problem with a single constraint, the equivalent unconstrained problem would read

$$\text{minimize}_{x \in \{0,1\}^n} x^\top Q x + \lambda f(x).$$

⁴This assumes the constraint coefficients are integer valued. For a treatment of the real-valued case see [8].

A suitable value for λ is crucial in ensuring both feasibility and quality. A value that is too small might result in infeasible solutions, while a value that is too large might dominate over the actual objective function and create a difficult optimization landscape, resulting in sub-optimal solutions. For some classes of problems, there are known bounds on the penalty values. For a discussion of QUBO modelling and penalty tuning of common optimization problems, we refer to [64] [65] and [66]. It must be noted that, in practice, the penalty parameter is often selected empirically, starting from a relatively small value and gradually increasing it until constraint satisfaction is reliably enforced without unduly distorting the objective landscape.

5.3 From QUBO to qubits

Once the problem has been expressed in QUBO form, it must still be adapted to the constraints of the underlying quantum hardware. As noted in Section 3.3, quantum annealers such as D-Wave's Advantage and Advantage2 systems arrange their qubits in specific hardware graphs (e.g., Chimera, Pegasus, or Zephyr), where each qubit can interact directly with only a small number of neighbors. This sparse connectivity contrasts sharply with the often dense interaction structure required by a QUBO. To reconcile this mismatch, the logical interaction graph of the QUBO must be represented in a form that the hardware graph can physically realize. This representation process is known as minor embedding. Minor embedding assigns each logical variable not to a single physical qubit, but to a chain. That is, a group of physical qubits that are linked together through strong ferromagnetic couplings. These couplings force the qubits in the chain to behave as a single unit, collectively representing the value of one logical variable. In essence, the chain acts as a "virtual" qubit that is connected in a way that supports the interactions required by the original QUBO.

The quality of an embedding depends heavily on chain length, coupling strengths, and how efficiently the chains are placed on the hardware. Longer chains are more susceptible to chain breaks, situations in which the physical qubits in a chain fail to align and thereby no longer represent a consistent logical value. Such breaks degrade solution quality and increase decoding overhead. Recent studies comparing multiple generations of D-Wave devices show that embedding quality directly impacts approximation ratios and chain-break rates, and that newer hardware topologies such as Zephyr help mitigate these issues by providing denser connectivity and enabling shorter, more robust chains [67].

Finding high-quality minor embeddings is itself a challenging computational task. In fact, determining an optimal embedding is NP-hard, meaning that heuristic and approximate algorithms are needed for all but the smallest problems. Because embedding directly affects chain length, qubit usage, solution robustness, and runtime, it often becomes a bottleneck in quantum-annealing workflows. Considerable research and engineering effort continues to go into developing better embedding algorithms, improving automated tools, and designing hardware topologies that reduce embedding overhead [44, 68].

6 Applications in Energy Systems (State of the Art)

This chapter reviews the state of the art in applying quantum computing to energy system problems. The focus is on concrete studies and demonstrated use-cases rather than speculative claims. In line with Chapter 2, the application areas discussed here are those in which energy systems exhibit large-scale complexity, uncertainty, non-convex decision structures, network constraints, or multi-timescale coupling. These characteristics are precisely what make many classical formulations computationally demanding and motivate the exploration of quantum approaches.

For each application area, the discussion is structured around five questions:

- i what is the underlying problem,
- ii how is it formulated,
- iii which quantum method is used,
- iv what has been demonstrated, and
- v what limitations remain.

6.1 Power System Operation and Unit Commitment

Problem: Unit commitment (UC) is one of the most important short-term operational problems in power systems. It determines which generating units should be switched on or off over a scheduling horizon while satisfying demand, reserve requirements, ramping limits, and technical operating constraints. As discussed in Chapter 2, UC is difficult because it combines binary decisions with continuous dispatch variables and becomes rapidly more complex when uncertainty, network constraints, or multiple time periods are included [20].

Formulation: Classically, UC is formulated as a mixed-integer linear program (MILP). In quantum studies, there are two predominant strategies. The first one consists of discretizing continuous variables in order to translate the entirety of the problem as a QUBO [69, 70]. Alternatively, a more common strategy is to isolate the binary commitment component from the continuous production variables and optimize them separately in an iterative fashion. This reflects a broader hybrid strategy in which the combinatorial core is targeted by a quantum method. Given the hardware limitations, a common simplification is to consider a single-period version of the UC problem.

Quantum method: As mentioned above, one possibility is to directly solve the UC problem by appropriately translating it into a QUBO formulation [69, 70]. This method, however, comes with scalability issues as the number of variables needed for the discretization can become prohibitive. Hybrid methods are also a well-studied alternative. Here, the problem is decomposed into (typically two) subproblems. A quantum computer is used to optimize over the binary

variables while keeping continuous variables fixed, while a classical computer performs the opposite task. There are several approaches to achieve such a hybrid, alternating method, for example, using the Surrogate Lagrangian Relaxation [71] or the Alternating Direction Method of Multipliers (ADMM) [72, 3]. The resulting QUBO is typically solved via QAOA. Another approach is the one of Aboumrad et al. [73] who use the quantum computer to sample binary strings corresponding to the commitment status by minimizing a surrogate function. An exhaustive search is then performed on the sampled vectors, for which the correct objective function is computed by solving the resulting quadratic continuous problem on a classical computer. Finally, an alternative hybrid approach is the one proposed by Paterakis [74], who solves the UC problem via Bender's decomposition. The role of the quantum computer is to aid in the cut selection process, which is formulated as either a set cover or a maximum coverage problem. For a more in-depth treatment of all the literature on quantum computing for unit commitment we refer to [13].

Results: The reviewed literature demonstrates the feasibility of applying quantum computing techniques to the UC problem. However, the reported results also reveal notable challenges related to scalability, particularly for approaches that discretize continuous decision variables. Hybrid quantum-classical methods exhibit better scalability, yet implementations based on QAOA remain constrained by the limited qubit counts of current gate-based quantum hardware. Despite these limitations, existing studies show that small-scale UC instances can be reliably solved and that feasible operational schedules can be produced. More broadly, the literature identifies UC as a promising target for quantum optimization due to its inherently binary decision structure [2, 7].

Limitations: Current demonstrations remain limited to small benchmark systems and simplified formulations. Realistic UC problems include many generators, many time periods, reserve requirements, startup logic, and often network constraints, making direct quantum treatment impractical on current hardware. Heavy classical preprocessing is still required, and no clear advantage over state-of-the-art MILP solvers has yet been established.

6.2 Grid Planning and Expansion

Problem: Grid planning and expansion problems arise at longer timescales and involve deciding where and when to build new generation, transmission, or flexibility assets. These are inherently multi-timescale and large-scale problems, since investment decisions must remain robust against long-term uncertainty while also supporting feasible short-term operation [15, 16]. The combinatorial nature of build/no-build decisions makes these formulations particularly challenging.

Formulation: Generation and transmission expansion planning are typically formulated as large-scale MILPs or stochastic optimization models with binary investment variables and continuous operational variables [75]. In quantum-oriented work, the binary planning layer is often viewed as the natural entry point for QUBO reformulation, while system simulation and operational validation remain classical [6].

Quantum method: Recent roadmap and perspective papers discuss hybrid quantum-classical approaches for power system planning, where quantum optimization is used to explore combinatorial investment choices and classical tools check technical and economic feasibility [6, 7].

Results: So far, the literature is mainly conceptual or proof-of-principle. The main contribution of existing studies is to show that planning decisions can, in principle, be mapped into quantum-

compatible formulations and embedded into broader classical planning workflows.

Limitations: Practical demonstrations of realistic transmission or generation planning models remain limited. Real planning problems include network constraints, uncertainty, representative periods, and many candidate projects, which can produce very large optimization models. Consequently, this area remains promising but immature from an implementation perspective.

6.3 Network-Constrained Optimization (Optimal Power Flow)

Problem: Optimal power flow (OPF) is the core network-constrained optimization problem in power systems. It determines a cost-minimizing operating point while satisfying physical laws and network limits. OPF becomes particularly difficult in AC form because of nonlinear and non-convex power flow equations [21]. Network-constrained problems also arise in redispatch, congestion management, contingency analysis, and security-constrained unit commitment.

Formulation: Most quantum applications in this area focus on simplified or discretized network models, especially DC power flow or discretized OPF variants. These are reformulated into QUBO or Ising forms so they can be solved with quantum annealers or related optimization hardware [21, 76].

Quantum method: In [4], a QUBO-based formulation of a DC power flow problem was demonstrated on a D-Wave quantum annealer. Related work has also explored discrete combinatorial formulations of power flow analysis using annealing-based hardware. For example, [76] formulated power flow analysis as a discrete combinatorial optimization problem and evaluated it on both quantum and digital annealers. Their results showed that feasible solutions can be obtained for small benchmark systems, while also highlighting discretization and scaling as key practical limitations.

Results: These studies showed that small network-constrained problems can be mapped to annealing hardware and solved successfully, providing an important proof of feasibility for applying quantum optimization to network-aware energy problems [2]. The main value of these studies lies in demonstrating that at least some power-system network problems can be cast into quantum-compatible form.

Limitations: The gap between simplified demonstrations and realistic OPF remains very large. AC-OPF is continuous, nonlinear, and non-convex, whereas current quantum optimization workflows typically require strong discretization and simplification. As a result, existing results are valuable as proof-of-concept, but they do not yet constitute a practical alternative to classical OPF solvers.

6.4 Renewable Integration and Hybrid Power Plants

Problem: Renewable-rich systems introduce major uncertainty and variability into operation and planning. Wind and solar generation are weather-dependent, and hybrid assets combining wind, solar, storage, and possibly hydrogen or other flexibility options create coupled decision problems across multiple timescales. These applications are particularly relevant because they combine stochasticity, binary choices, and inter-temporal operation.

Formulation: Such problems are typically formulated as stochastic or robust optimization models, often with scenario-based uncertainty representations. When hybrid assets are considered, the model may also include mixed-integer decisions related to charging, curtailment, reserve activation, or asset commitment.

Quantum method: A quantum computing approach for stochastic economic dispatch in renewables-rich power systems is introduced in [5]. More broadly, recent review and perspective papers identify renewable integration and hybrid system scheduling as promising areas for hybrid quantum-classical optimization [2, 7].

Results: The main result from this line of work is that quantum methods may help address the combinatorial and scenario-driven complexity introduced by high renewable penetration, especially in stochastic dispatch settings. These studies extend the quantum discussion beyond deterministic toy problems to applications that more closely reflect the uncertainty characteristics of modern power systems.

Limitations: Current studies remain small-scale and strongly dependent on simplified formulations, classical preprocessing, and limited scenario sets. Real-world hybrid plant optimization accounts for nonlinear efficiencies, degradation effects, detailed market participation, and plant-level control interactions, which are not yet captured in most quantum demonstrations.

6.5 Energy Markets and Bidding Strategies

Problem: Electricity markets solve large-scale optimization problems to match supply and demand while respecting market rules and, in some cases, network constraints. These problems may involve integer bid structures, cross-border power exchanges, reserve coupling, and strict solution time requirements [26]. The combinatorial nature of block bids and market coupling makes these problems computationally demanding, particularly in large interconnected systems such as the European electricity market. For example, the European day-ahead market coupling algorithm (EUPHEMIA) solves a very large mixed-integer optimization problem to clear bids across multiple countries under strict time constraints.

Formulation: Market-clearing problems are typically formulated as welfare-maximizing linear or mixed-integer optimization models. Quantum-oriented research primarily focuses on discrete decision components, such as combinatorial bidding structures or hierarchical decision problems, that can be reformulated as QUBO-like structures suitable for quantum optimization.

Quantum method: Recent literature explores hybrid quantum-classical approaches for market analysis, including stochastic market decision-making and multi-stage bidding problems [7]. Some studies also investigate quantum-assisted frameworks for simulating electricity and carbon markets, in which quantum optimization components are integrated into larger classical decision-making pipelines.

Results: Recent work has begun to explore quantum-assisted approaches to electricity market analysis and decision-making. For example, [77] proposed a hierarchical quantum-classical framework for simulating multi-timescale electricity and carbon markets, demonstrating how quantum optimization could support complex market decision processes. Other exploratory studies combine quantum computing and machine learning techniques to evaluate uncertainty in electricity market behavior [78].

Limitations: Despite these developments, most existing studies remain exploratory and rely on simplified market models rather than real market-clearing engines. Modern electricity markets

already rely on highly optimized large-scale algorithms operating under strict computational deadlines. Consequently, there is currently no convincing evidence that quantum approaches outperform advanced classical market-clearing methods in realistic operational settings [2, 6, 7].

6.6 Energy Storage Scheduling

Problem: Energy storage scheduling determines how storage assets should charge, discharge, and participate in electricity markets over time. These problems are inherently inter-temporal, since the state of charge links decisions across multiple time steps. The problem becomes more complex when multiple storage units interact with stochastic renewable generation, market price uncertainty, or multiple market layers such as energy, reserves, and ancillary services [2].

Formulation: Storage scheduling is typically formulated as a mixed-integer or dynamic optimization problem, depending on the modeling detail and market structure. Binary decisions may represent operational modes or market-participation choices, whereas continuous variables represent charging, discharging, and state-of-charge dynamics. When multiple assets and uncertainties are considered, these formulations can become large-scale multi-period optimization problems.

Quantum method: Quantum optimization approaches have been proposed to address the combinatorial aspects of storage scheduling. Simple versions of the problem can be modeled using the QUBO formulation and solved directly on quantum hardware [9]. In settings with multiple interacting storage assets or stochastic operating conditions, most proposed approaches rely on hybrid quantum-classical frameworks in which discrete decision variables are mapped to QUBO formulations, while continuous system dynamics are evaluated using classical solvers [2, 7].

Results: Existing studies suggest that energy storage management could become a relevant application domain for hybrid quantum-classical workflows, particularly when embedded within broader renewable-integration or market-optimization frameworks. Early work on quantum computing highlighted both the potential and the challenges of applying it to energy storage analysis and system optimization [79].

Limitations: Compared to applications such as unit commitment or simplified power flow problems, quantum research on storage scheduling remains relatively limited. Realistic storage optimization models often include battery degradation effects, nonlinear efficiency curves, and detailed market participation rules, which are difficult to translate directly into quantum-ready formulations. Consequently, most current studies remain conceptual and have not yet demonstrated advantages over classical optimization approaches.

6.7 Energy Network Reliability

Problem: In the context of energy grid operation, network reliability is of utmost importance. A common constraint is ensuring that the power grid can continue delivering electricity if any single connection unexpectedly fails. This requirement is commonly known as N-1 security. As electricity demand grows and grid infrastructures expand, operators must evaluate increasingly large and complex networks. However, checking N-1 security becomes computationally burdensome because the number of failure scenarios and the associated calculations grow with network size, making timely and scalable assessment difficult as grids evolve.

Formulation: For each of the potential single-element failures, a contingency plan must be computed which must satisfy a number of so-called load flow constraints. This gives rise to a constrained non-linear optimization problem for each possible failure.

Quantum method: The role of quantum computing for the N-1 problem has been investigated by Neumann et al. [80]. Here the authors study three quantum approaches. The first one is implemented using gate-based quantum computing, where the N-1 problem is formulated as unstructured search and solved via Grover's algorithm. On a second instance, they formulate the problem as a QUBO with appropriate penalties to impose the load flow constraints and the tree-like structure of valid configurations. A third approach consisted in using Gaussian Photon Sampling in order to find reconfigurations.

Results: The authors find that while all three quantum approaches can formally encode the N-1 reconfiguration problem, their practical performance varies significantly. Gate-based quantum search demonstrates conceptual feasibility but is limited to very small instances due to current hardware constraints. Quantum annealing performs more robustly, successfully solving the QUBO-encoded formulations and showing comparatively better scaling on existing devices. In contrast, the photonic Gaussian sampling method does not yield competitive results: its sampling distribution fails to consistently produce valid reconfigurations, making it markedly less effective for structured N-1 search. Overall, none of the quantum methods outperform classical techniques at realistic system sizes.

Limitations: The complex flow constraints associated with the N-1 problem seem to pose the largest challenge when formulating this problem for quantum computing. The work of Neumann et al [80] indicates that further research is necessary to be able to solve problems at the required scale.

6.8 Overview of Quantum-Energy Application Studies

Table 6.1 and Table 6.2 summarize representative studies reviewed in this report, grouped by application area, quantum approach, and level of maturity. The overview highlights an important pattern across the literature: most current work focuses on discrete optimization subproblems that can be reformulated as QUBO or Ising models, while highly continuous and strongly constrained problems remain significantly more difficult to address with current quantum hardware.

The reviewed studies also show the dominant role of hybrid quantum-classical workflows. In most practical demonstrations, quantum methods are not used as standalone solvers, but rather as specialized components embedded within larger classical optimization or simulation pipelines. This reflects the limitations of current Noisy Intermediate-Scale Quantum (NISQ) hardware, including restricted qubit counts, limited connectivity, noise sensitivity, and embedding overheads.

6.9 Summary

The literature shows that quantum computing has been explored across several important energy-system applications, including unit commitment, grid planning, power flow analysis, renewable integration, electricity markets, energy storage scheduling, and network reliability assessment. These applications correspond closely to the computational challenges identified

Table 6.1: Representative optimization-oriented quantum-energy studies reviewed in this report.

Application Area	Representative Studies	Quantum Approach	Main Contribution / Focus	Maturity
Unit commitment	[3, 12, 71]	QAOA, hybrid decomposition	UC-oriented QUBO and hybrid scheduling formulations	Proof-of-concept
Power flow and OPF	[4, 76]	Annealing, QUBO reformulation	DC power flow and simplified OPF demonstrations	Prototype
Grid planning and expansion	[6, 81]	Hybrid optimization	Discrete investment and planning formulations	Exploratory
Energy storage scheduling	[9]	QUBO, annealing	Storage scheduling optimization	Prototype
Distributed generation	[10, 11]	QUBO optimization	Distributed generation coordination	Prototype

Table 6.2: Representative system-level, stochastic, and benchmarking quantum-energy studies reviewed in this report.

Application Area	Representative Studies	Quantum Approach	Main Contribution / Focus	Maturity
Renewable integration and stochastic dispatch	[5]	Hybrid stochastic optimization	Quantum-assisted stochastic dispatch under renewable uncertainty	Exploratory
Electricity markets and bidding	[77, 78]	Hybrid optimization, QML	Market optimization and uncertainty analysis	Exploratory
Network reliability and contingency analysis	[80]	Grover search, annealing, photonic sampling	N-1 contingency reconfiguration and search	Prototype
Survey and benchmarking studies	[2, 7, 82]	Review and benchmarking frameworks	Assessment of scalability, benchmarking, and applicability of QC in energy systems	Review

in Chapter 2, particularly large-scale optimization, uncertainty handling, combinatorial decision-making, network constraints, and multi-period coordination.

At the same time, the reviewed studies reveal a strong concentration around discrete optimization problems and QUBO-compatible formulations. Problems with dominant binary structures, such as unit commitment subproblems, switching decisions, contingency filtering, and selected planning tasks, currently represent the most realistic application areas for near-term quantum methods. In contrast, highly continuous and nonlinear problems, such as full AC optimal power flow or integrated planning-operation formulations, remain poorly aligned with current hardware and algorithmic capabilities.

The maturity of the reviewed application areas also varies significantly. Unit commitment and simplified network optimization currently have the clearest proof-of-concept demonstrations, while planning, markets, stochastic workflows, storage scheduling, and reliability applications remain largely exploratory. Across nearly all application domains, the most credible results rely on hybrid quantum-classical architectures rather than standalone quantum solutions [2, 6, 7].

A second key observation is that scalability challenges are not driven solely by hardware limitations. Problem formulation, embedding efficiency, constraint handling, and benchmarking

methodology are equally important bottlenecks. Many current demonstrations require strong simplifications, aggressive discretization, or limited benchmark systems, making it difficult to assess whether practical quantum advantage can realistically emerge for large-scale energy applications.

Overall, the literature indicates that quantum computing can be meaningfully connected to selected energy-system optimization problems, particularly those with combinatorial structure. However, there is currently no convincing evidence that quantum methods outperform advanced classical optimization techniques for realistic large-scale system operation or planning. Near-term value is therefore most likely to emerge through carefully designed hybrid workflows that target specific computational bottlenecks rather than attempting full replacement of existing energy-system optimization pipelines.

7 Benchmarking, Limitations, and Practical Readiness

7.1 Performance Metrics and Benchmarking against Classical Methods

Benchmarking quantum algorithms is a challenging task. Traditional digital complexity metrics, typically based on floating point operations, do not map cleanly onto the continuous, probabilistic, and hardware-dependent dynamics of quantum systems. Quantum algorithms often produce stochastic outputs that require extensive sampling to estimate performance reliably, while noise, device variability, and compiler-dependent transpilation introduce non-deterministic overheads that classical baselines do not share. Moreover, benchmarking is highly sensitive to problem encoding choices, and parameter-tuning strategies, all of which vary widely across studies and are often underreported, making comparisons inconsistent and potentially misleading. These challenges are amplified when it comes to methods that utilize hybrid hardware solutions.

The recent report by Phillipson [82] presents these challenges in more detail, while also stressing the importance of standardized reporting, diverse problem sets, and transparency in tuning and hardware conditions. The report outlines a number of recommendations that aim to mitigate the risk of overstating performance or suggesting unwarranted quantum advantage, ultimately undermining reproducibility and comparability across the field.

7.2 Scalability, Hardware, and Formulation Constraints

Scalability is the central limitation for quantum applications in energy systems. The number of qubits required to encode realistic models typically exceeds available hardware. Beyond qubit count, qubit connectivity or qubit noise can also become limiting factors. This is a symptom of the current technological context: today's machines belong to the Noisy Intermediate-Scale Quantum (NISQ) era. The “intermediate-scale” label reflects that platforms can host a limited number of qubits, while “noisy” refers to the imperfect control, decoherence, and gate errors that impact computation. Active research across academia and industry continues to push all of these architectures forward, but none currently achieves fully error-corrected, large-scale operation, a highly sought-after goal for most quantum hardware developers (see Figure 7.1).

While progress in the application of quantum computing is strongly tied to hardware developments, algorithmic improvements also play a key role. Most importantly, the literature reviewed in this report points toward one core message: smart modeling and translation of problem constraints is of the essence to ensure scalability of the algorithms.

A frequent oversight in assessing the performance of gate-based quantum algorithms is the treatment of data encoding. Since information is naturally stored and maintained in classical memory, and quantum states are too fragile for persistent storage, any quantum routine must begin by translating classical inputs into quantum states. Numerous encoding schemes exist,

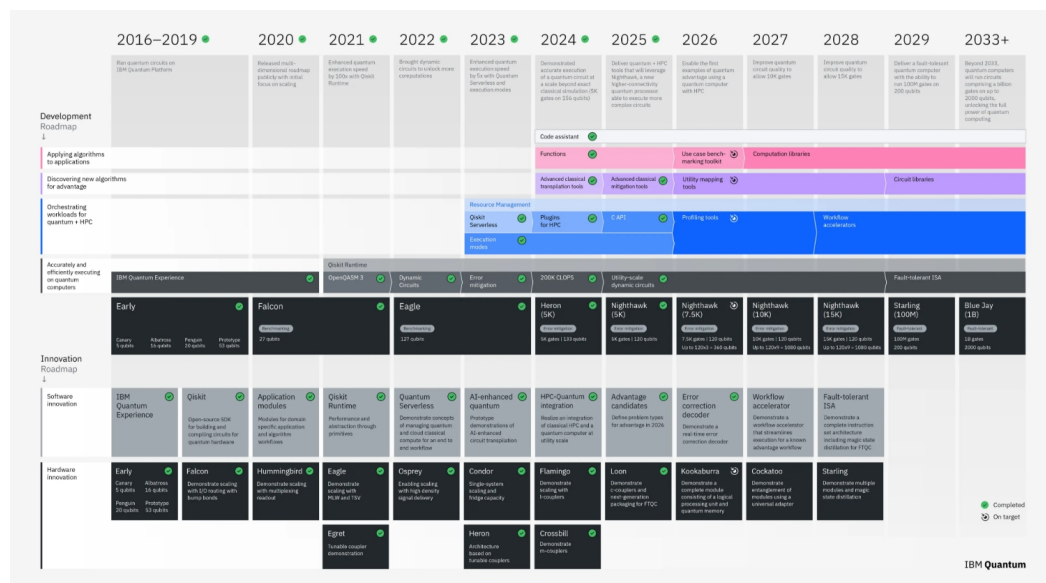


Figure 7.1: IBM Quantum roadmap of hardware development. Taken from [83].

e.g. rotation-based encodings or amplitude-based encodings, but the act of preparing the corresponding quantum state can itself be computationally demanding. In fact, generating a general quantum state may require a number of gates that grows exponentially with the dimension of the data unless the input possesses specific structure, meaning that state preparation alone can dominate the overall cost of the algorithm.

7.3 Pathways Toward Practical Quantum Advantage

While progress is being made in quantum computing applications for energy systems, the work surveyed in this report shows that many challenges still exist in deploying this technology in real-world settings. Current demonstrations are largely confined to small-scale or stylized problem instances, and practical deployments must account for hardware noise, encoding overheads, and the difficulty of scaling quantum formulations to realistic system sizes. Taken together, these observations allow us to identify structural properties of optimization problems that either align well with the capabilities of near-term quantum devices or, conversely, highlight inherent limitations.

Problems that exhibit the following characteristics are generally more amenable to quantum approaches:

- Optimization problems with a large proportion of binary variables. Quantum computers operate natively on binary decision variables. When a problem's structure is already binary, little reformulation is required, reducing mapping overhead and enabling algorithms to exploit the combinatorial nature of the search space.
- Problems that are naturally quadratic. Quadratic formulations such as QUBOs or Ising models directly match the energy landscapes implemented by annealing hardware and the objective forms typically required by quantum optimization algorithms. When cost functions can be expressed as pairwise interactions without extensive higher-order terms,

embedding becomes significantly more efficient and circuit depth requirements remain manageable.

In contrast, problems with the characteristics below tend to be more challenging for current quantum technologies:

- Naturally continuous-valued. Many energy system models involve continuous decision variables (e.g., generator dispatch levels, voltage magnitudes). Encoding these into binary representations suitable for quantum algorithms requires discretization, often inflating problem size and introducing large numbers of auxiliary variables. This not only increases qubit requirements but can also distort the original problem structure, reducing the likelihood of meaningful quantum gains.
- Highly constrained. Real-world energy problems are often rich in operational constraints. Translating these constraints into binary quadratic penalties generally leads to dense cost matrices or large penalty coefficients, both of which strain current hardware. Embedding dense constraint structures on annealers or implementing deep circuits to encode them on gate-based devices can quickly exceed device capabilities, making the resulting formulations impractical.

This is not to say that problems exhibiting the aforementioned characteristics should be disregarded. Rather, such problems necessitate a departure from the prevalent one-to-one translation into a QUBO formulation, favoring instead approaches that treat quantum resources as specialized accelerators embedded within broader hybrid optimization workflows. This perspective enables a decoupling of the effective problem size from hardware limitations by restricting quantum processing to appropriately selected subproblems of the original formulation.

7.4 Research Gaps

In summary, several critical gaps emerge from the literature.

A first gap is the lack of **realistic large-scale validation**. Most studies remain limited to simplified benchmark systems, reduced formulations, or stylized proof-of-concept examples. As a result, there is still limited understanding of how quantum methods behave under realistic energy-system conditions involving large networks, operational constraints, uncertainty, and multi-period coupling.

A second gap lies in **problem formulation and mapping**. Current QUBO-based formulations often lead to dense, inefficient representations that limit scalability and negate potential benefits. More efficient, structure-preserving mappings are largely missing.

A third gap is the absence of **realistic benchmarking**. There is a lack of standardized test systems, consistent performance metrics, and transparent reporting, making it difficult to assess real progress or compare results across studies.

A fourth gap concerns the representation of **real-world operational complexity**. Important aspects such as market interactions, regulatory constraints, uncertainty management, and multi-actor coordination are often heavily simplified or excluded, limiting the practical relevance of current demonstrations.

8 Conclusions and Future Directions

This literature review presents the growing body of work in applications of quantum computing to a variety of problems in energy systems. Across the surveyed areas, existing studies demonstrate that quantum methods can capture the combinatorial structure inherent to many energy challenges, and that small proof-of-concept instances can be solved using available quantum hardware. However, the findings also make clear that practical deployment has not been reached: current algorithms scale poorly beyond toy systems, continuous variables must be discretized, and hardware characteristics limit solution quality. The timeline for practical applicability therefore remains uncertain, as realistic large-scale energy applications would likely require substantially higher effective qubit counts and lower noise levels than currently available hardware provides.

Two structural observations are central. First, problems dominated by binary decisions and naturally quadratic formulations are the most compatible with quantum hardware, as they can be mapped to QUBO or Ising models with minimal overhead. This explains why unit commitment and investment planning remain the primary focus of current studies. Second, problems that are continuous or highly constrained remain much more difficult: discretization inflates qubit requirements, constraint penalties lead to dense interactions, and embedding such structures exceeds the connectivity and coherence capabilities of today's devices. As a result, the most promising progress has come from hybrid quantum-classical frameworks, where quantum routines address limited combinatorial subproblems while classical solvers handle continuous or network-constrained components.

Equally important is the development of standardized benchmarking practices [82], including transparent reporting of hardware conditions, encoding choices, parameter-tuning efforts, and computational overheads, to ensure fair comparison against classical baselines. The engagement of both the quantum and energy systems communities is required to ensure fair benchmarking on problems of practical relevance.

Finally, as hardware evolves toward higher qubit counts, improved connectivity, and reduced noise, the feasible scale of quantum subproblems will increase. In parallel, the most realistic near-term impact of quantum computing in the energy domain lies in incremental enhancements within hybrid workflows, rather than full replacement of classical solvers. Overall, quantum computing holds promise for selected layers of energy system optimization, but realizing this potential will require continued progress in algorithms, hardware, and benchmarking, alongside careful alignment of problem structures with the strengths of emerging quantum technologies.

8.1 Answering the Core Research Questions

This review addressed the research questions introduced in Chapter 1, Section 1.5, concerning the relevance, applicability, limitations, and practical adoption pathways of quantum computing in energy systems.

1. First, regarding *which classes of energy system problems are structurally compatible with quantum computing*, the evidence indicates that the most credible opportunities lie in discrete, combinatorial subproblems embedded within larger system workflows. These include unit commitment substructures, network switching decisions, contingency screening, and selected investment planning decisions.
2. Second, regarding *whether realistic quantum advantage can be achieved under current limitations*, current evidence does not support a practical advantage for realistic system sizes. Any potential advantage is highly conditional on problem structure, formulation efficiency, and hybrid integration with classical methods.
3. Third, regarding *the dominant technical and formulation-related bottlenecks*, the literature shows that the main limitations are not only hardware-related, but also structural: inefficient problem mappings, constraint encoding overhead, and the mismatch between continuous system physics and discrete quantum formulations.
4. Fourth, regarding *which hybrid quantum–classical approaches appear most promising*, the literature consistently points toward decomposition-based and hybrid optimization architectures, where quantum methods target combinatorial cores while classical solvers maintain feasibility, continuous optimization, and system-level integration.
5. Finally, regarding *the pathway toward practical adoption*, the evidence suggests that near-term progress will most likely come through incremental integration into existing workflows, targeted pilot applications, and rigorous benchmarking against state-of-the-art classical approaches, rather than through standalone quantum solutions.

8.2 Use Cases and Application Potential

Based on both literature evidence and system characteristics, the most promising application areas can be categorized as follows:

High potential (near-term, hybrid):

- Decomposed unit commitment (binary scheduling subproblems)
- Network switching and reconfiguration in distribution grids
- Contingency selection and screening (e.g., N-1 filtering)
- Discrete investment decisions in expansion planning

These applications share a common structure: a dominant combinatorial core with limited coupling to continuous variables, making them suitable for QUBO-based formulations or variational quantum optimization within hybrid workflows.

Moderate potential (mid-term, conditional on algorithmic and hardware progress):

- Scenario reduction and uncertainty sampling
- Stochastic dispatch subproblems (decomposed formulations)
- Simplified market bidding strategies

These applications may benefit from quantum approaches in sampling, scenario exploration, or combinatorial substructures, but require further advances in problem decomposition, encoding efficiency, and hardware scalability to demonstrate practical value.

Low near-term suitability (under current NISQ limitations):

- Full AC optimal power flow
- Detailed dynamic simulations
- Fully integrated planning-operation models

These problems are dominated by continuous variables, nonlinear physics, and dense constraints, making them poorly aligned with current quantum formulations. While they may become partially tractable in the long-term with fault-tolerant quantum computing and improved algorithms, there is currently no clearly demonstrated pathway toward practical quantum advantage for these applications.

8.3 Market Perspective and Partner Motivations

From a market and stakeholder perspective, interest in quantum computing is driven by increasing computational pressure in energy systems. Transmission System Operators (TSOs), energy developers, and regulators are facing growing challenges related to scalability, uncertainty, and system complexity, particularly in planning under high renewable penetration, congestion management, and stochastic operation. However, market consultation inputs indicate a clear expectation: *solutions must be credible, incremental, and integrable into existing workflows*. There is limited appetite for disruptive or standalone quantum solutions that cannot demonstrate clear added value over current tools or that require complete redesign of operational pipelines.

Key motivations from stakeholders include:

- Improving scalability of planning and operational tools (e.g., large-scale UC, expansion planning)
- Handling uncertainty more efficiently (scenario management, probabilistic assessment)
- Enhancing decision support under increasing system complexity (multi-asset, multi-timescale coordination)
- Exploring future-proof computational capabilities without compromising current reliability

At the same time, there is strong skepticism toward over-claimed quantum advantage. Stakeholders require clear evidence of benefit relative to advanced classical methods, including transparent benchmarking, reproducibility, and integration feasibility.

At present, there is limited evidence that quantum approaches produce solutions of higher practical optimality than advanced classical methods for realistic energy-system problems. Current studies primarily demonstrate feasibility rather than measurable improvements in operational cost or system performance. Near-term value is therefore expected to arise mainly from improved computational tractability for selected combinatorial subproblems.

This creates a fundamental tension. While quantum computing is perceived as a potential long-term enabler, its near-term value must be demonstrated through targeted, well-defined use cases embedded within existing workflows. As a result, hybrid quantum–classical approaches aligned with concrete operational or planning challenges are significantly more likely to gain stakeholder acceptance than standalone quantum solutions.

8.4 Strategic Direction and Future Projects

Based on the identified gaps and opportunities, future work should focus on a limited number of high-impact and application-driven directions:

Hybrid solution architectures (primary focus): Develop decomposition frameworks where quantum methods are embedded within classical optimization workflows (e.g., Benders decomposition, column generation, ADMM, surrogate-based coordination). The objective is to isolate combinatorial subproblems that can be treated by quantum routines while preserving full system feasibility through classical solvers.

Efficient problem mappings: Design structure-aware formulations that minimize qubit requirements, reduce constraint overhead, and exploit sparsity. Particular emphasis should be placed on avoiding dense penalty formulations and preserving the original problem structure to ensure scalability.

Benchmarking and validation: Establish standardized test cases and evaluation protocols aligned with realistic energy system applications. This includes transparent comparison against state-of-the-art classical solvers, sensitivity to encoding choices, and reproducibility across hardware platforms.

Tool integration (application layer): Integrate quantum components into existing energy modeling tools (e.g., EMERGE, TNO's hybrid power plant energy management system modeling environment, or TULIPA, an optimization framework for large-scale energy system modeling) rather than developing standalone solutions. This enables direct evaluation of added value within operational and planning workflows.

Targeted pilot projects (proof of value): Focus on well-defined use cases with measurable impact, such as contingency screening, reduced unit commitment formulations, and discrete planning subproblems. These pilots should demonstrate clear performance, scalability, or decision-quality improvements relative to classical baselines.

8.5 Positioning and Future Ambition

The role of applied research organizations is not to develop quantum hardware, but to bridge the gap between theoretical advances and real-world energy system applications. This requires a system-level perspective that connects algorithmic developments to operational, market, and regulatory contexts.

This includes:

- Translating energy system problems into quantum-compatible formulations while preserving physical and operational relevance

- Designing hybrid quantum–classical architectures that are aligned with real system workflows (planning, operation, and markets)
- Validating performance against realistic system models, including uncertainty, network constraints, and multi-timescale interactions
- Providing independent, system-level assessment of emerging quantum technologies, avoiding vendor-specific bias and purely theoretical claims

This positioning helps ensure that quantum computing developments remain aligned with actual system needs and market requirements. The long-term ambition is to establish a credible pathway for integrating quantum methods into energy-system workflows where they provide measurable added value.

8.6 Final Outlook

Quantum computing should not be viewed as a replacement for classical energy system optimization, but as a potential *specialized computational accelerator* for selected problem components. In the near term, its impact will be incremental and realized within hybrid quantum–classical workflows. In the longer term, advances in hardware and algorithms are expected to increase the size and complexity of tractable subproblems. However, the dominant factor will remain the structure of the problem and the efficiency of its formulation, rather than raw computational power alone.

Ultimately, the success of quantum computing in energy systems will depend on the ability to identify and target specific components of system-level decision-making where it delivers measurable added value, while remaining fully integrated within existing operational and planning workflows.

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