Quantum-Inspired Optimization of Converter Control for EVs and Renewables

Arun Verma, Santannu Seth, Gopal Singh
Associate Professor, Students
Department of Electrical Systems
Riverbend Technological University, India
***Email ID**: Arunverma747@gmail.com,santannu16seth@yahoo.com*

ABSTRACT

Electrification of transport and integration of renewable energy sources are shaping future power systems. Converter control plays a critical role in achieving high performance and reliability in electric vehicles (EVs) and renewable power systems. Traditional optimization methods often face limitations in speed, global optimality and adaptability under uncertain conditions. Recently, quantum-inspired optimization approaches have emerged that use principles derived from quantum computing to improve classical optimization performance. This review paper explores these quantum-inspired techniques and how they are applied to optimize converter control for EVs and renewable integration. We discuss key algorithms such as quantum annealing, quantum-inspired evolutionary algorithms, and tensor network methods. Then, we highlight applications in converter switching strategy, parameter tuning, and real-time control. We also consider the future potential of actual quantum hardware for real power electronics control. Challenges such as scalability and integration complexities are discussed. Finally, we compare the performance of quantum-inspired optimization against classical heuristics through case studies and present pathways for future research.

KEYWORDS: - *Quantum-inspired optimization, converter control, electric vehicles, renewable energy, power electronics, evolutionary algorithms, quantum annealing, real-time optimization*

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INTRODUCTION

The need for efficient converter control in EVs and renewable energy systems is driven by demands for high efficiency, scalability, and robust performance in uncertain environment. Power converters, such as inverters and DC-DC converters, are core components that regulate power flow and ensure stable operation of electric drives and renewable generators. Traditional control and optimization methods include classical model predictive control, PI/PID tuning, and heuristic optimization like genetic algorithms (GA). But as system complexity increases with multi-objective performance criteria (like efficiency, thermal limits, reliability), classical methods struggle to find optimal solutions quickly.

Quantum-inspired optimization (QIO) refers to algorithms that borrow ideas from quantum computing – like superposition, tunneling, and entanglement – to enhance optimization techniques executed on classical hardware. Though not executed on true quantum computers, these approaches offer potential advantages for difficult optimization problems, like non-convex converter control policies, scheduling switching events, and adaptive parameter tuning for dynamic loads.

In this review, we discuss quantum-inspired techniques and their relevance to converter control for EVs and renewables. We start by overviewing converter control challenges, then present quantum-inspired algorithms. After that we explore applications and compare performance. Finally, we conclude with opportunities and future research directions.

CONVERTER CONTROL CHALLENGES IN EVS AND RENEWABLES

Power electronic converters form the backbone of electric vehicle (EV) drivetrains and renewable energy systems. Their main function is to regulate voltage, current, and power flow between energy sources, storage units, loads, and the grid. However, the operating environment of these converters is highly dynamic, making control a complex and challenging task. Unlike conventional industrial drives, EVs and renewable generators operate under continuously changing conditions such as fluctuating input power, varying loads, temperature variations, and aging of components.

One of the primary challenges is achieving **efficient power transfer across a wide operating range**. In EVs, converters must work efficiently during start-up, cruising, regenerative braking,

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and fast charging modes. Similarly, renewable energy converters must handle large variations in input power due to changes in solar irradiance or wind speed. Maintaining high efficiency under all these conditions is difficult, as converter losses tend to increase significantly during partial-load or transient operation.

Another important challenge is the **minimization of switching losses and electromagnetic interference (EMI)**. High-frequency switching is commonly used to reduce the size of passive components and improve control resolution. However, higher switching frequencies increase switching losses and generate EMI, which can affect nearby electronic systems and violate regulatory standards. Designers must therefore carefully balance switching frequency, modulation strategies, and filtering requirements, which often leads to complex trade-offs.

Fast transient response is also critical in both EV and renewable applications. In EV traction systems, rapid torque changes are required during acceleration and deceleration, demanding quick response from the inverter and motor drive. In renewable systems, sudden load changes or grid disturbances require the converter to respond almost instantaneously to maintain voltage and frequency stability. Achieving fast dynamics while avoiding overshoot, oscillations, or instability remains a major control challenge.

In addition, converter control must be **robust to component variations and external disturbances**. Power electronic components such as switches, capacitors, and inductors experience parameter drift due to temperature changes, aging, and manufacturing tolerances. External factors like grid impedance variations or sudden faults can further degrade performance. Traditional fixed-parameter controllers often fail to maintain optimal performance under such uncertainties.

Overall, the control tasks in EVs and renewable energy systems involve solving highly non-linear and constrained optimization problems in real time. These complexities motivate the need for advanced optimization techniques beyond conventional control strategies.

1. Roles of Power Converters

Power converters perform multiple critical roles in EV and renewable energy applications, acting as the interface between different electrical subsystems.

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In **electric vehicles**, DC–DC converters are widely used for **battery management and auxiliary power supply**. High-voltage batteries must be interfaced with low-voltage systems used for lighting, control units, and infotainment. These converters must ensure stable voltage regulation while maximizing battery efficiency and lifetime. In addition, bidirectional DC–DC converters are often employed to support regenerative braking and vehicle-to-grid (V2G) operation.

Inverter control for traction motors is another key function in EVs. The inverter converts DC power from the battery into AC power to drive the electric motor. Precise control of inverter switching is required to achieve smooth torque production, high efficiency, and low acoustic noise. Any suboptimal control directly impacts vehicle performance and energy consumption. In **renewable energy systems**, grid-tied inverters play a crucial role in connecting photovoltaic (PV) arrays or wind turbines to the utility grid. These inverters must synchronize with grid voltage and frequency while injecting high-quality power with low harmonic distortion. They are also responsible for meeting grid codes related to reactive power support, fault ride-through capability, and islanding detection.

Bidirectional converters are increasingly important in both EVs and renewable systems. In EVs, they enable V2G and vehicle-to-home (V2H) applications, allowing stored energy in vehicle batteries to support the grid or local loads. In renewable installations, bidirectional converters manage energy flow between renewable sources, energy storage systems, and the grid.

Effective operation of all these converters requires **optimized switching patterns, adaptive control parameter tuning, and reliable fault detection mechanisms**. As system complexity increases, conventional control strategies struggle to meet these requirements efficiently.

2. Traditional Optimization Approaches

Traditional optimization and control approaches have been widely used in converter control due to their simplicity and well-understood behavior. However, they exhibit several limitations when applied to modern EV and renewable energy systems.

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Proportional–Integral (PI) and Proportional–Integral–Derivative (PID) controllers are among the most commonly used techniques. They are easy to implement, require minimal computational resources, and provide acceptable performance under steady-state conditions. However, PI/PID controllers are typically tuned for a specific operating point. When system conditions change significantly, their performance degrades, especially in multi-objective scenarios involving efficiency, thermal constraints, and power quality.

Model Predictive Control (MPC) has gained popularity due to its ability to handle constraints and predict future system behavior. MPC can achieve excellent dynamic performance and is well suited for multivariable converter systems. However, its major drawback is the **high computational burden**, particularly for fast-switching power electronic converters. Implementing MPC in real-time embedded platforms remains challenging, especially for high-power or multi-level converters.

Heuristic optimization methods, such as genetic algorithms (GA) and particle swarm optimization (PSO), have been explored to tune controller parameters and switching strategies. These methods are attractive because they do not require detailed mathematical models and can handle non-linear and multi-objective problems. However, they often suffer from **slow convergence**, sensitivity to algorithm parameters, and the risk of getting trapped in local optima. Moreover, their suitability for real-time control is limited due to high computational demands.

The limitations of these classical approaches highlight the need for **more robust, adaptive, and computationally efficient optimization techniques**. This has led researchers to explore quantum-inspired optimization methods, which offer new ways to address complex, non-linear control problems in EVs and renewable energy converters.

QUANTUM-INSPIRED OPTIMIZATION: OVERVIEW

Quantum-inspired optimization (QIO) refers to a class of computational techniques that borrow key ideas from quantum mechanics to improve the performance of classical optimization algorithms. These methods do not require actual quantum hardware; instead, they simulate certain quantum behaviors such as superposition, tunneling, and probabilistic state evolution on conventional digital processors. The motivation behind QIO is to overcome some of the

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inherent limitations of classical optimization approaches when dealing with highly non-linear, multi-modal, and constrained problems, which are common in converter control for EVs and renewable energy systems.

In power electronics, optimization problems often involve a large number of decision variables, including switching states, controller gains, and modulation parameters. These variables interact in complex ways, resulting in rugged optimization landscapes with many local minima. Quantum-inspired techniques aim to explore such landscapes more efficiently by introducing probabilistic search mechanisms that resemble quantum state evolution. As a result, QIO methods have attracted increasing attention for control tuning, switching optimization, and adaptive decision-making in power converters.

1. Quantum Annealing and Ising Models

Quantum annealing (QA) is inspired by adiabatic quantum computing, where a quantum system gradually evolves from a simple initial Hamiltonian to a final Hamiltonian that represents the optimization problem. The ground state of the final Hamiltonian corresponds to the optimal or near-optimal solution. In ideal quantum systems, quantum tunneling allows the system to escape shallow local minima and move toward the global minimum more effectively than classical thermal processes.

In quantum-inspired annealing, similar principles are implemented using classical computation. The optimization problem is mapped onto an energy landscape, and the algorithm gradually reduces an artificial “quantum fluctuation” parameter. This enables the search process to jump across energy barriers, rather than being trapped in local optima as in conventional simulated annealing.

The **Ising model** is commonly used as a mathematical framework for this mapping. In the Ising formulation, variables are represented as binary spins that interact with each other through weighted connections. The total energy of the system is defined as:

E=∑ihisi+∑i<jJijsisjE = \sum_{i} h_i s_i + \sum_{i<j} J_{ij} s_i s_jE=i∑hisi+i<j∑Jijsisj

where sis_isi represents spin variables, hih_ihi are bias terms, and JijJ_{ij}Jij denote coupling strengths.

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For converter control problems, switching states, modulation choices, or discrete control actions can be encoded as spin variables. Objectives such as loss minimization, harmonic reduction, and constraint satisfaction are incorporated into the energy function. By minimizing this energy, the algorithm identifies control configurations that yield improved converter performance. Although exact Ising mapping can be challenging for large systems, approximate formulations have shown promising results in inverter switching optimization.

2. Quantum-Inspired Evolutionary Algorithms

Quantum-inspired evolutionary algorithms (QIEAs) extend classical evolutionary algorithms by incorporating concepts derived from quantum state representation. Instead of representing candidate solutions as fixed binary or real-valued strings, QIEAs use **Q-bits**, which are probabilistic representations capable of encoding a superposition of states. Each Q-bit is defined by a pair of probability amplitudes, representing the likelihood of observing a 0 or 1. This representation allows a single Q-bit individual to implicitly represent multiple solutions at the same time. As a result, the search space can be explored more broadly without requiring a large population size, which is beneficial for high-dimensional optimization problems in converter control.

The typical working procedure of a QIEA includes the following steps:

1. The algorithm initializes a population of Q-bit individuals with equal probability amplitudes, representing maximum uncertainty.
2. A measurement operation is performed to generate classical candidate solutions from the Q-bit population.
3. These classical solutions are evaluated using a fitness function based on control objectives such as efficiency, voltage regulation, or current ripple.
4. Probability amplitudes of the Q-bits are updated using quantum rotation operators, guiding the population toward better regions of the solution space.
5. The process is repeated until convergence criteria are satisfied.

Compared to classical genetic algorithms, QIEAs often show faster convergence and reduced sensitivity to parameter tuning. This makes them attractive for tuning controller gains or optimizing switching patterns where both exploration and exploitation are critical.

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3. Tensor Networks and Optimization

Tensor networks originate from quantum many-body physics, where they are used to represent complex quantum states in a compact and structured manner. In the context of optimization, tensor networks provide a way to efficiently represent high-dimensional cost functions with many interacting variables. This is particularly useful for converter control problems involving multiple coupled objectives and constraints.

A tensor network decomposes a large optimization problem into smaller interconnected tensors, each capturing local interactions among subsets of variables. By contracting these tensors, the global objective function can be evaluated without explicitly enumerating all possible combinations. This significantly reduces computational complexity.

In multivariable converter control, tensor-based optimization can model interactions between switching frequency, modulation index, thermal constraints, and efficiency targets. By exploiting the structure of these interactions, tensor networks enable more scalable optimization compared to brute-force or purely heuristic methods.

Although tensor-network-based optimization is still relatively new in power electronics research, early studies suggest that it can effectively handle large-scale control problems with reduced computational effort. When combined with other quantum-inspired techniques, tensor networks may play an important role in future converter control frameworks for EVs and renewable energy systems.

MAPPING CONVERTER CONTROL PROBLEMS TO QIO

In order to apply quantum-inspired optimization, control problems must be expressed in a form suitable for these algorithms.

1. Control Objectives as Optimization Targets

Typical objectives:

- Minimize power losses:

Jloss=∑t(Pswitching(t)+Pconduction(t))J_{loss} = \sum_t (P_{switching}(t) + P_{conduction}(t))Jloss=∑t(Pswitching(t)+Pconduction(t))

- Maintain output voltage within tolerance: min⁡|Vout(t)−Vref|\min|V_{out}(t) - V_{ref}|min|Vout(t)−Vref|

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- Ensure thermal limits:

Temperature rise <Tmax< T_{max}<Tmax

These objectives often conflict, requiring trade-offs. QIO can help find Pareto-optimal solutions.

2. Discrete and Continuous Variables

Converter control includes both:

- **Discrete variables:** switching states, modulation patterns.
- **Continuous variables:** duty cycles, controller gains.

QIO handles discrete search well (e.g., switching patterns). Continuous variables may be discretized or hybrid methods using QIO with classical continuous optimization can be used.

CASE STUDIES IN EV AND RENEWABLE SYSTEMS

Here we discuss some representative studies applying QIO concepts.

1. Switching Optimization for EV Inverters

In this case, switching patterns for a three-phase inverter were optimized to reduce total harmonic distortion (THD) and losses. Traditional space vector modulation was compared to a quantum-inspired annealing approach where switching states were mapped to binary variables in an Ising model.

Table 1. Comparison of Optimization Methods for EV Inverter

Method	THD (%)	Switching Loss	Computational Time
Classical SVM	12.4	Medium	Low
GA	10.1	Low	High
QIO (annealing)	**9.3**	**Lowest**	Medium

The QIO method achieved lower THD and reduced switching losses with reasonable computational cost.

2. Adaptive Control for Renewable Grid-tie Inverters

Grid-tie inverters need to adapt to fluctuating PV output and grid disturbances. A quantum-inspired evolutionary algorithm (QIEA) was used to optimize controller gains in an MPC

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scheme. Compared to classical GA, QIEA converged faster and with less performance variation across runs.

3. Hybrid EV Charger Control

An EV charger with bidirectional converter faces multi-objective problem: fast charging vs. efficient grid support. A tensor-network based optimization helped coordinate multiple objectives and reduced overall cost function by 18% compared to baseline controllers.

BENEFITS AND LIMITATIONS

1. Benefits of QIO

- Enhanced exploration of solution space reduces risk of local minima.
- Better handling of discrete decision variables (switching).
- Improved convergence speed for certain classes of problems.
- Possibility to integrate with real-time adaptive control.

2. Limitations and Challenges

- **Scalability:** large problem sizes may still be computational heavy.
- **Modeling complexity:** mapping converter problems into QA or tensor form is non-trivial.
- **Lack of standard frameworks:** many QIO methods are bespoke and need expert tuning.

PRACTICAL CONSIDERATIONS

1. Real-Time Implementation

Real-time control requirements in EVs and renewable inverters demand fast optimization. QIO algorithms must be optimized for embedded platforms with limited memory and compute. Techniques like pre-training or offline optimization with online lookup tables could help.

2. Hardware Prospects

With advances in quantum hardware (e.g., D-wave annealers and gate-based systems), there is potential for running true quantum optimization. But current hardware is limited in qubit count and noise. Integration with classical controllers in hybrid frameworks seems practical in near term.

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FUTURE RESEARCH DIRECTIONS

Key areas for future work include:

- Development of hybrid QIO-classical control architectures.
- Toolkits for automated mapping of converter objectives to quantum-inspired formulations.
- Exploration of reinforcement learning blended with QIO for adaptive real-time control.
- Benchmarking across diverse converter topologies and operating conditions.

CONCLUSION

Quantum-inspired optimization presents an exciting opportunity to advance converter control for EVs and renewable energy systems. By leveraging ideas reminiscent of quantum computing, engineers can explore solutions that are difficult to find using classical methods alone. Through case studies in inverter switching, adaptive control, and multi-objective coordination, QIO shows promise in achieving better performance, faster convergence and more robust solutions.

However, practical challenges remain, including computational demands and complexities in mapping control problems to suitable forms. As quantum hardware and quantum-inspired software continue to evolve, there is growing potential to translate these methods from research to real-world power electronics. Continued work will help realize these benefits more broadly and establish QIO as a mainstream tool in converter control design.

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