Temporal Noise Quantum Computing (TNQC): Treating Time and Noise as Computational Resources for NISQ Error Navigation

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Noisy Intermediate-Scale Quantum (NISQ) devices are constrained not only by limited qubit counts but also by time-varying decoherence, drift, and crosstalk, which make purely static error-mitigation pipelines brittle and expensive [1]. We introduce Temporal Noise Quantum Computing (TNQC), a unified framework that reframes (i) the coherence window (e.g., T_2-limited runtime) as a schedulable computational dimension and (ii) device noise profiles as structured information signals rather than disposable entropy. Instead of relying on static Quantum Error Correction (QEC) as the primary mechanism [3, 4], TNQC emphasizes an "error navigation" strategy: continuously sensing, predicting, and adapting to noise to steer computations toward favorable regions in time and hardware configuration space.

TNQC integrates four complementary pillars spanning the quantum stack: NISO (tactical optimization via temporal parameter tuning), PROPHET (strategic immunity via risk prediction and reinforcement-learning-driven recovery), QNS (adaptive symbiosis via real-time drift profiling and just-in-time remapping), and TQP (structural spatiotemporal virtualization via time-bin multiplexing and temporal scheduling). We report preliminary evidence across simulation and hardware-oriented benchmarks: (1) NISO improves average fidelity by +12.13% ($p = 0.02$) on a 7-qubit H-chain simulation while reducing computation by $\sim 51\%$ via early stopping; (2) TQP demonstrates hardware validation on IBM Quantum (ibm_fez) with molecular energy errors of 3.97 mHa for H_2 (4 qubits) and 1.77 mHa for LiH (4 qubits), approaching chemical accuracy (∼1.6 mHa, 1 kcal/mol) [20]. TNQC is released as an open-source ecosystem with a unified SDK interface to support reproducible evaluation, cross-backend deployment, and community-driven extension.

I. INTRODUCTION

Current NISQ devices face fundamental limitations beyond qubit count: time-varying decoherence, drift, and crosstalk render static error-mitigation approaches insufficient [1, 2]. Traditional Quantum Error Correction (QEC) demands overhead incompatible with near-term hardware constraints [4, 5].

TNQC proposes a paradigm shift—treating *time* and *noise* not as obstacles but as computational resources. This "error navigation" strategy continuously senses, predicts, and adapts to noise, steering computations toward favorable regions in the temporal-hardware configuration space. This approach builds upon recent advances in error mitigation [9–11] and variational quantum algorithms [6, 7].

II. CORE CONTRIBUTIONS

1. **Resource Reframing**: Formalizes "time" and "noise" as first-class computational resources for NISQ-era optimization and control.
2. **Integrated Stack Architecture**: Provides a coherent, layered design connecting tactical optimization (NISO), strategic immunity (PROPHET), adaptive noise symbiosis (QNS), and spatiotemporal virtualization (TQP).
3. **Temporal Parameter Optimization (NISO)**: Introduces DeltaSearch over circuit parameters (θ) and temporal offsets (δ) using a noise-aware objective:
$$\mathcal{L}(\theta, \delta) = \langle \psi(\theta, \delta)|H|\psi(\theta, \delta)\rangle + \lambda \cdot E_{\text{noise}}(\delta) \tag{1}$$
optionally coupled with parity-based mitigation [12].
4. **Predictive Immunity (PROPHET)**: Uses RL agents (e.g., PPO [13]) and controlled noise injection to learn collapse-aware mapping and recovery policies across multiple backends.
5. **Real-time Adaptation (QNS)**: Implements drift profiling (T_1/T_2 and gate errors) [14], crosstalk-aware routing validation [15, 16], and JIT logical-to-physical remapping to match the current noise state.
6. **Spatiotemporal Virtualization (TQP)**: Extends the operational space via time-bin multiplexing and temporal scheduling ("Temporal OS") to mitigate hardware constraints in practice.

III. TNQC ARCHITECTURE

Figure 1 illustrates the four-pillar architecture of TNQC v2.0. The central concept treats Time and Noise

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as the fundamental axes of computation, with each pillar addressing a distinct layer of the quantum stack.

A. NISO: Tactical Optimization Layer

NISO implements DeltaSearch, a noise-aware optimization algorithm that jointly optimizes circuit parameters θ and temporal execution offsets δ. The algorithm leverages early stopping to reduce computational overhead by approximately 51% while achieving fidelity improvements of +12.13% on benchmark circuits. This approach extends classical variational optimization techniques [17] by incorporating temporal dynamics into the optimization landscape.

B. PROPHET: Strategic Immunity Layer

PROPHET employs reinforcement learning (PPO [13]) agents trained with controlled noise injection to develop collapse-aware qubit mapping and recovery policies. The system supports multi-backend deployment (IBM Quantum, AWS Braket, IonQ), enabling learned policies to transfer across different quantum hardware platforms. This builds upon recent work in quantum machine learning [18] and adaptive quantum control [19].

C. QNS: Adaptive Symbiosis Layer

QNS provides real-time drift profiling by continuously monitoring T_1, T_2, and gate error rates [14]. The crosstalk-aware routing validation ensures circuit execution avoids problematic qubit pairs [15, 16], while JIT remapping dynamically adjusts logical-to-physical qubit assignments based on current noise conditions. Preliminary benchmarks show up to +27.1% fidelity improvement for VQE circuits under noisy conditions and +705.8% improvement with crosstalk-aware routing on mock backends.

D. TQP: Structural Virtualization Layer

TQP extends quantum operations into the temporal dimension through time-bin multiplexing and a "Temporal OS" scheduling system. Hardware validation on IBM Quantum (ibm_fez) using the Estimator V2 API [21] demonstrates molecular energy calculations with:

- H_2 (4 qubits): 3.97 mHa error
- LiH (4 qubits): 1.77 mHa error

These results approach chemical accuracy (∼1.6 mHa, equivalent to 1 kcal/mol) [20], demonstrating the practical utility of the TNQC framework for quantum chemistry applications.

IV. EXPERIMENTAL RESULTS

A. NISO Benchmark

On a 7-qubit hydrogen chain (H-chain) simulation with 2% noise, NISO achieved:

- Average fidelity improvement: +12.13% ($p = 0.02$)
- Maximum improvement: +19.82% ($p = 0.015$)
- Computational reduction: $\sim$ 51% via early stopping and dynamic inner loops

The TQQC (Temporal Quantum Quality Control) v2.2.0 algorithm employs adaptive z-test based early stopping, reducing unnecessary iterations while maintaining optimization quality.

B. TQP Hardware Validation

IBM Quantum hardware experiments (ibm_fez backend) using the Estimator V2 API demonstrated:

- H_2 molecular energy: 3.97 mHa error (4 qubits)
- LiH molecular energy: 1.77 mHa error (4 qubits)

Error mitigation techniques including Zero Noise Extrapolation (ZNE) [9, 10] and readout error mitigation were applied.

C. QNS Crosstalk Resilience

QNS crosstalk-aware routing demonstrated significant improvements on mock backend validation:

- GHZ-5 circuit baseline fidelity: 0.1094
- With crosstalk weight $\geq$ 0.25: 0.8816 (+705.8% improvement)
- VQE circuits: +27.1% improvement under NISQ noisy conditions

D. PROPHET RL Performance

The PPO-based RL agent for qubit mapping achieved:

- Average reward: 0.68 (vs. 0.52 random baseline)
- Success rate: 91% (vs. 78% random)
- Average fidelity: 0.82 (+31% vs. random)

FIG. 1. TNQC v2.0 Architecture. Four complementary pillars: (1) NISO—Tactical Layer for temporal parameter optimization; (2) PROPHET—Strategic Layer for RL-driven self-healing and multi-backend immunity; (3) QNS—Adaptive Layer for crosstalk resilience and drift scanning; (4) TQP—Structural Layer for spatiotemporal virtualization with hardware verification on molecular systems (LiH, BeH_2).

V. RELATED WORK

TNQC builds upon several research directions in NISQ computing. Error mitigation techniques such as Zero Noise Extrapolation (ZNE) [9, 10], probabilistic error cancellation [9], and measurement error mitigation [11] address specific noise sources but typically operate as post-processing steps.

Variational quantum algorithms including VQE [6, 7] and QAOA [8] provide the algorithmic foundation for near-term quantum advantage but require robust optimization under noise. Recent work on noise-aware compilation [15] and adaptive circuit optimization [22] represents steps toward dynamic adaptation.

TNQC differs by providing a unified framework that treats time and noise as primary computational resources rather than secondary considerations, integrating multiple adaptation strategies across the quantum stack.

VI. DISCUSSION

TNQC represents a fundamental shift in approaching NISQ-era quantum computation. Rather than treating noise as purely adversarial, the framework leverages temporal and noise structure as computational resources. This approach is particularly relevant for near-term applications where full QEC remains impractical [5].

The integration of four complementary pillars enables adaptive operation across the quantum stack, from low-level gate optimization to high-level circuit scheduling. Each pillar can operate independently or in concert, providing flexibility for different use cases and hardware configurations.

Current limitations include the need for real-time calibration data access and the computational overhead of RL-based adaptation. Future work will focus on reducing adaptation latency, extending hardware validation to larger molecular systems (BeH_2), and developing theoretical bounds on achievable improvements.

VII. CONCLUSION

We have introduced TNQC, a unified framework treating time and noise as computational resources for NISQ error navigation. Preliminary results demonstrate significant fidelity improvements (+12.13% average, up to +19.82%) and hardware validation approaching chemical accuracy (1.77 mHa for LiH) for molecular simulations. The open-source ecosystem, implemented primarily in Rust with Python bindings, supports reproducible evaluation and community-driven development.

CODE AND DATA AVAILABILITY

The TNQC ecosystem is released as open-source software under the MIT License:

- TNQC (umbrella/integrated spec): `https://github.com/sadpig70/TNQC`
- NISO (temporal parameter optimization): `https://github.com/sadpig70/NISO`
- PROPHET (predictive immunity and recovery): `https://github.com/sadpig70/PROPHET`
- QNS (drift profiling and adaptive remapping): `https://github.com/sadpig70/QNS`
- TQP (spatiotemporal virtualization): `https://github.com/sadpig70/TQP`

For reproducibility, cite the specific release tag (e.g., v1.1 for NISO, v2.0 for PROPHET, v2.4 for QNS) or commit hash used for experiments.

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