B. Miska., Vol 2(2), pp 88-97
https://doi.org/10.55306/CJDTES.2025.020202
e-ISSN: 3048-8389
Ci-STEM Journal of Digital Technologies and Expert Systems

A Study of Quantum-Inspired Signal Processing for Future Communication Systems

Balaiah Miska
Tata Communications Transformation Services Ltd. Pune, India
email: balaiah.miska@tatacommunications.com.

Open Access
Review Article
Received: 30/05/2025
Accepted: 16/07/2025
Published: 23/08/2025

Corresponding author email:
balaiah.miska@tatacommunications.com.

Citation:
Miska. B., "A Study of Quantum-Inspired Signal Processing for Future Communication Systems" Ci-STEM Journal of Digital Technologies and Expert Systems, Vol. 2(2), pp. 88-97, 2025.
doi: 10.55306/CJDTES.2025.020202

Copyright:
©2025 Miska. B.,
This is an open-access article distributed under the terms of the Creative Commons Attribution License which grants the right to use, distribute, and reproduce the material in any medium, provided that proper attribution is given to the original author and source, in accordance with the terms outlined by the license.
(https://creativecommons.org/licenses/by/4.0/)
.

Published By:
Ci-STEM Global Services Foundation, India.

Abstract:
Networks built to sixth-generation (6G) targets will have to hold sub-millisecond latency, push spectral efficiency past what today's massive MIMO deployments achieve, and manage resources across highly heterogeneous nodes with little human supervision. Those targets place a hard demand on the optimizer. Channel estimation, adaptive modulation, beamforming and decoding all involve searching large, non-convex parameter spaces, and the search has to finish inside a coherence interval that may last only a few hundred microseconds. This paper surveys quantum-inspired signal processing (QISP), a family of classical algorithms that borrow structure from quantum computation, including amplitude-weighted superposition sampling, quantum-walk-style exploration, Ising-model formulations and tensor-network compression, but that run entirely on conventional processors. We group the literature under four headings: algorithmic foundations, communication-system architectures, optimization strategies, and implementation constraints. We then propose a reference architecture in which a quantum-inspired optimization engine sits beside a conventional OFDM/MIMO transmit-receive chain and reconfigures modulation, beam-selection and decoding parameters from channel-state feedback. An illustrative simulation grounds the discussion: a representative QISP optimizer is compared against a conventional adaptive baseline over a 4×4 MIMO, QPSK, AWGN-channel OFDM link at signal-to-noise ratios (SNR) from 0 to 20 dB. These numbers demonstrate methodology and are not measurements taken from physical hardware. Within that caveat, the QISP optimizer achieves a lower bit-error rate (BER) at low and moderate SNR, and the throughput and latency trends are consistent with the parameter-search efficiency reported in the wider literature. The paper concludes with open problems such as scalability, algorithmic complexity, explainability and standardized benchmarking, and research directions on hybrid quantum-classical processors, reconfigurable intelligent surfaces (RIS), semantic communications, and edge-native QISP inference.

Keywords:
Quantum-inspired computing, signal processing, 6G wireless networks, combinatorial optimization, MIMO, OFDM, adaptive modulation, tensor networks, machine learning for communications, reconfigurable intelligent surfaces..

1. INTRODUCTION

No generation of mobile standards has been defined by a single breakthrough. What separates each one from the last is accumulated optimization capability: sharper channel estimates, finer-grained resource allocation, and faster adaptation to a radio environment that never holds still. The 6G targets now under discussion press that capability hard. Terabit-per-second peak rates, sub-millisecond air-interface latency, ubiquitous sensing and largely autonomous network management all sit awkwardly with conventional adaptive filtering and convex optimization. Part of the difficulty is structural. Joint beam and modulation selection across a large antenna array is a combinatorial problem, and exact solutions stop being reachable once the antenna, user and subcarrier counts begin to grow.

Quantum computing offers a route through such spaces, at least in principle, by way of amplitude amplification [2] and quantum parallelism [1], [3]. Hardware capable of running those algorithms fault-tolerantly, at communication scale and inside communication timescales, remains some years away [23]. Quantum-inspired signal processing occupies the ground in between. It borrows the

mathematical structure of quantum algorithms, including probability amplitudes, superposition-style candidate sampling, rotation-gate update rules and tensor-network representations, and implements that structure in ordinary floating-point arithmetic. Since no quantum hardware is involved, QISP methods can be deployed today in baseband processing units, edge servers or RAN intelligent controllers, and they still tend to outperform purely classical heuristics on the same optimization problems.

Three contributions follow. The first is a structured synthesis of recent QISP work for communications, organized as a taxonomy over algorithmic foundations, system architectures and optimization strategies. The second is a reference system architecture that embeds a quantum-inspired optimization engine inside a conventional OFDM/MIMO transceiver chain, together with a description of that engine as a closed-loop search-evaluate-update process. The third is an illustrative, reproducible simulation study comparing a representative QISP optimizer against a conventional adaptive baseline across a range of SNR values, supported by block diagrams, conceptual illustrations and performance graphs. The remainder of the paper is arranged as follows. Section 2 reviews related work and Section 3 sets out QISP fundamentals. Section 4 presents the proposed framework and Section 5 gives its mathematical formulation. Section 6 describes the simulation methodology, and Sections 7 and 8 cover open challenges and future directions. Section 9 concludes.

2. LITERATURE REVIEW

QISP is theoretically grounded in two foundational quantum algorithms. Shor's factoring algorithm [1] and Grover's search algorithm [2] showed that quantum mechanical resources could yield, for certain classes of problems, exponential or quadratic speed-ups over the best-known classical methods at the time. Later, Nielsen and Chuang [3] developed the linear-algebraic framework of state vectors, unitary operators and measurement. That was the paradigm that classical algorithms simulated when they wanted to mimic the quantum search behavior without physical qubits.

From the point of view of communications, the starting point is the classical adaptive-filtering and estimation theory summarized by Haykin [4], together with the information-theoretic treatment of wireless channels given by Goldsmith [5] and by Tse and Viswanath [6]. The work of Larsson et al. [7] on Massive MIMO increased the dimension of the beamforming and detection problems and made the case for optimization methods that have a better scaling than exhaustive or purely gradient-based approaches. Han and Kim [22] proposed quantum-inspired evolutionary algorithms, in which candidate solutions are represented in terms of quantum-bit-inspired probability amplitudes and updated by rotation-gate-like operators. "Much of the subsequent literature on QISP optimizers in communications is based on that update rule [20]."

Since then, application-specific studies have been conducted along several directions: channel estimation [18], MIMO detection [19], sparse-signal recovery based on the principles of compressive sampling [12], and beamforming [13]. Tensor-network methods [11] have a different goal, compressing high-dimensional channel-state information prior to optimization, so the effective search dimensionality is reduced. We return to this in Section 3.3. Simultaneously, there is a larger body of work on nature-inspired metaheuristics, such as swarm- and evolution-based optimizers [14], [21], [22], for resource allocation in wireless networks. One can reasonably read QISP as a specialization within that family, one that borrows specifically quantum-flavoured update rules and representations.

Machine learning refers to an overlapping and complementary direction. O'Shea and Hoydis [15] and Zhang et al. [25] show that learned representations of the physical layer adapt to channel conditions in a way that is resistant to hand-engineering. Recent surveys [8], [20] explicitly place QISP as a bridge between classical adaptive algorithms and future hybrid quantum-classical processors. The motivation at the system level stems from 6G vision papers [9] and 5G disruptive-technology overviews [24], where ultra-low latency, massive connectivity, and network intelligence are exactly the reasons to chase faster optimization primitives. Two emerging areas recur throughout this literature and return in Section 9: reconfigurable intelligent surfaces (RIS) [16] and semantic or task-oriented communication [17]. Both add combinatorial or high-dimensional design variables of the kind QISP-style optimizers handle well.

3. FUNDAMENTALS OF QUANTUM-INSPIRED SIGNAL PROCESSING

QISP techniques share one strategy. A communication-system optimization problem is mapped onto a high-dimensional search space, and that space is then explored using update rules taken from quantum computation, with every state variable and every operation remaining classical. Four building blocks recur across the literature.

3.1 Amplitude-Weighted Candidate Representation

A candidate solution, say a modulation-and-beam configuration, is not stored as a single deterministic value. QISP methods store it instead as a pair of probability amplitudes, analogous to the superposition coefficients of a qubit. Sampling from that representation yields a whole population of candidates on each iteration, which gives the search a degree of parallel exploration that a single-point classical heuristic does not have.

3.2 Rotation-Gate-Inspired Update Rules

Once the fitness of the sampled candidates has been evaluated, whether by resulting BER, throughput or a weighted combination of the two, the amplitude pair for each variable is nudged toward the amplitudes associated with the better performers. The update rule is structurally similar to a quantum rotation gate. With each iteration, the amplitude distribution shifts weight toward high-fitness regions of the search space. This behavior mirrors the amplitude amplification found in Grover's algorithm [2], even though the underlying mechanics rely strictly on standard floating-point operations.

Figure 1 makes the practical consequence visible. A single greedy trajectory, shown on the left, follows one path uphill and settles wherever that path happens to lead. Amplitude-weighted sampling, shown on the right, advances several candidates at once and therefore probes more than one basin of the landscape before committing.

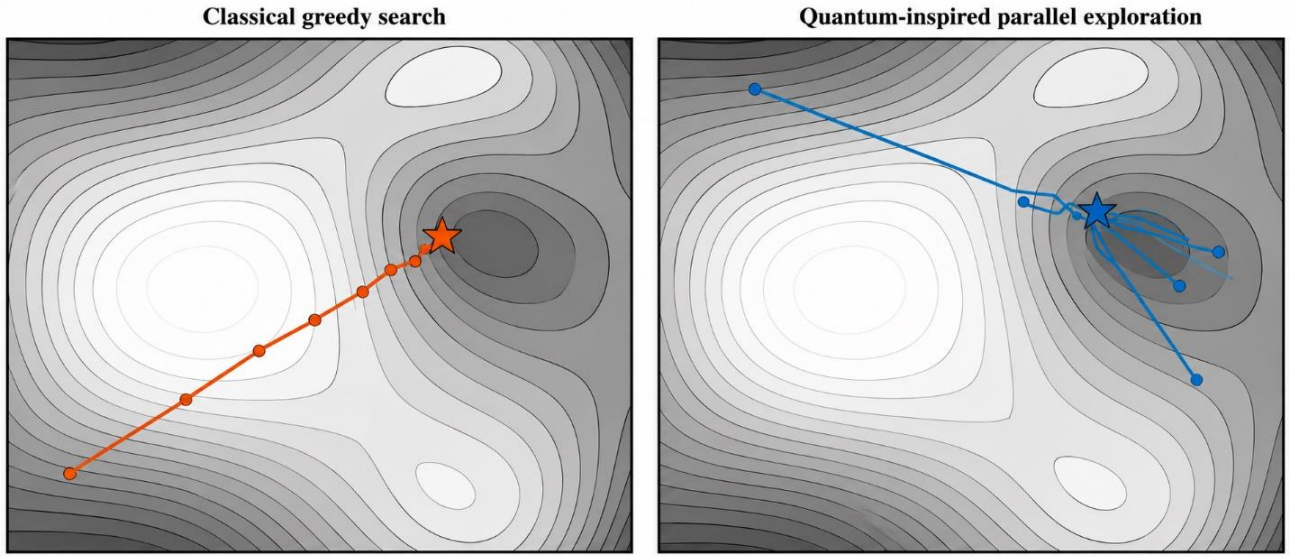


Figure 1. Conceptual comparison of solution-space exploration. A single greedy trajectory (left) is contrasted with amplitude-weighted parallel sampling (right), which reaches near-optimal regions in fewer iterations.

3.3 Ising-Model and Tensor-Network Formulations

Discrete beam selection, subcarrier assignment and similar combinatorial subproblems can often be recast as Ising-model energy minimization. The formulation has a long history in statistical physics and is also what quantum annealers consume. Even with no annealing hardware present, classical Ising solvers gain from the reformulation, because it exposes problem structure such as pairwise interaction terms that generic solvers can exploit.

Tensor-network decompositions [11] address a different bottleneck. Figure 2 shows the idea: a high-dimensional channel-state tensor is factored into a short chain of lower-rank core tensors, so the optimizer searches a far smaller space than the raw channel-state information would imply.

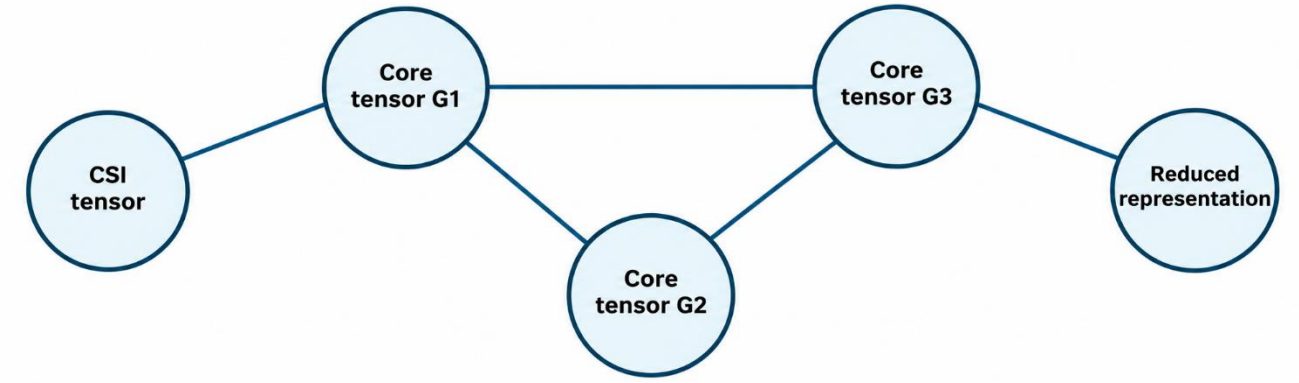


Figure 2. Tensor-network decomposition used to compress high-dimensional channel state information (CSI) before quantum-inspired optimization, reducing the effective search dimensionality.

3.4 Randomized Linear Algebra

Continuous subproblems, least-squares channel estimation being the obvious example, are frequently handled with randomized linear algebra: randomized sketching, randomized SVD and related techniques. These trade a small and bounded increase in estimation variance for a large reduction in computational cost. That trade becomes attractive whenever channel estimates have to be refreshed within a coherence interval of a few hundred microseconds.

4. PROPOSED FRAMEWORK

Figure 3 shows the proposed reference architecture. A conventional transmit chain (adaptive modulation, OFDM waveform generation and MIMO precoding), a wireless channel model, and a conventional receive chain (MIMO/OFDM detection and channel decoding) are augmented with a quantum-inspired optimization engine that sits outside the real-time symbol-processing datapath. The engine consumes channel-state feedback and post-detection performance metrics from the receiver, then periodically issues updated control parameters: modulation order per subcarrier, beam-selection indices, and decoding parameters such as iteration counts or LLR scaling. Keeping the engine off the symbol datapath matters. The latency-critical path stays simple and deterministic, while the optimizer runs on a slower control-plane timescale, which is how RAN intelligent controllers are already structured in current network architectures.

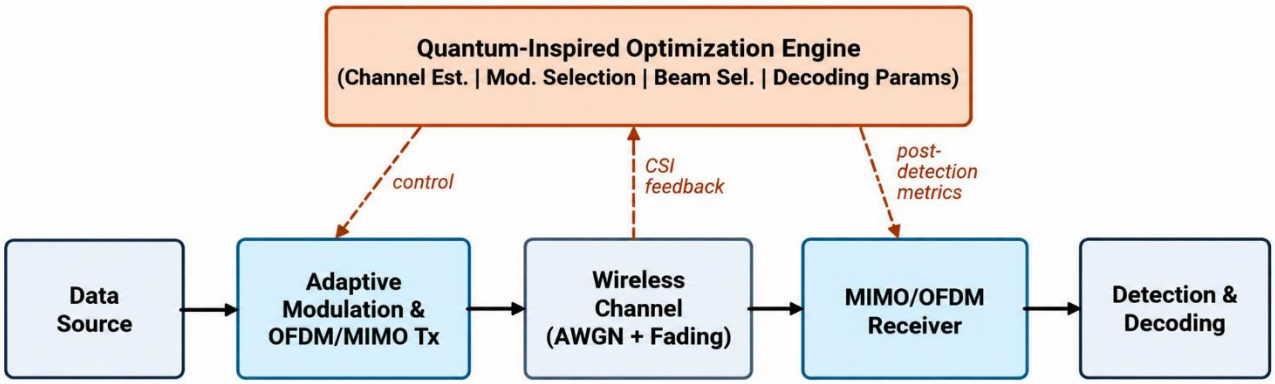


Figure 3. Proposed end-to-end system architecture. A quantum-inspired optimization engine sits above the transmit-receive chain and continuously reconfigures modulation, beam and decoding parameters.

Figure 4 opens up the engine itself as a closed-loop, six-stage process. Stage 1 initializes a population of candidate parameter vectors as amplitude pairs. Stage 2 draws sampled candidate vectors from that amplitude-weighted distribution, in the spirit of superposition-inspired search. Stage 3 evaluates each candidate against the objective defined in Section 5, which weighs BER against throughput under a power constraint. Stage 4 updates every variable's amplitude pair using

the rotation-gate-inspired rule, favouring amplitudes tied to higher-fitness candidates. Stage 5 tests convergence, either fitness improvement falling below a threshold or exhaustion of the iteration budget. Stage 6 outputs the best candidate, which becomes the parameter vector applied to the transmit-receive chain. A failed convergence check returns the loop to stage 2 with the updated amplitude distribution.

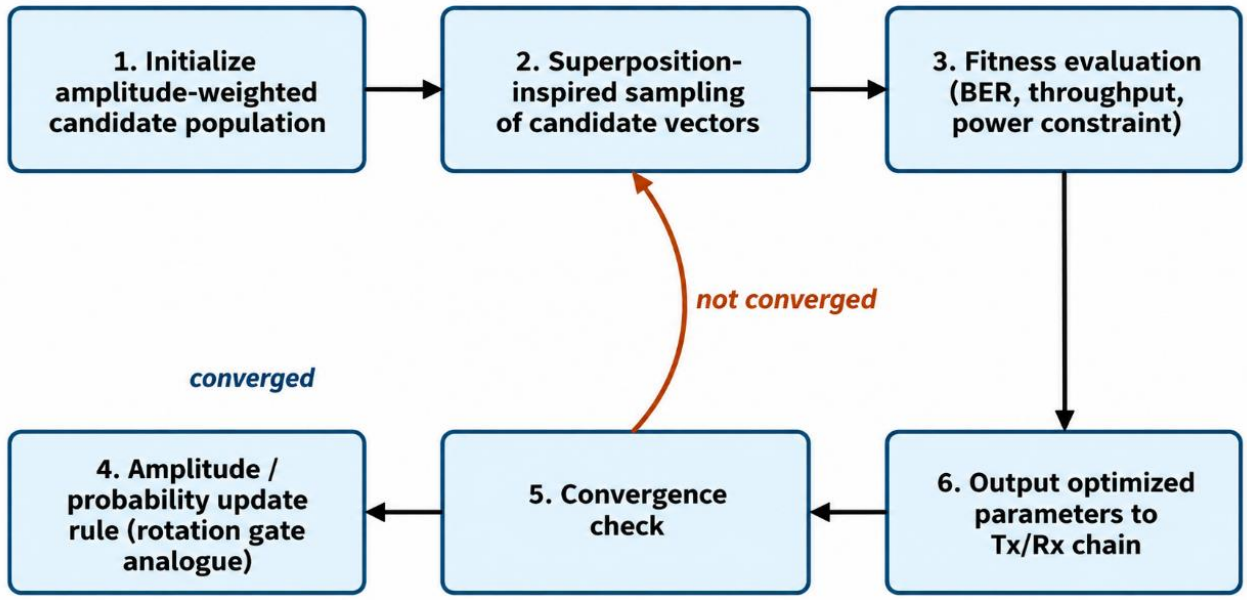


Figure 4. Internal structure of the quantum-inspired optimization engine used for channel estimation, modulation, beam selection and decoding-parameter search.

The design is deliberately modular. The fitness function in stage 3 and the amplitude-update rule in stage 4 can be swapped independently of one another, so the same control loop serves channel estimation, adaptive modulation, beam selection or decoding-parameter tuning. Only the objective and the candidate encoding change; the surrounding control logic does not.

4.1. Mathematical Formulation

For a spatial-multiplexing MIMO-OFDM link, the baseband received signal on each subcarrier is modelled as

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n} \tag{1}$$

where x is the transmitted symbol vector, H the channel matrix, n additive white Gaussian noise, and y the received symbol vector. Figure 5 illustrates H conceptually for the 4×4 array used in the simulation study of Section 6.

The optimizer balances two goals that pull against each other, low bit-error rate and high throughput, under a transmit power constraint. Scalarizing the pair gives the cost

$$J(\boldsymbol{\theta}) = \alpha\,\mathrm{BER}(\boldsymbol{\theta}) - \beta\,R(\boldsymbol{\theta}) \tag{2}$$

and the constrained search problem

$$\boldsymbol{\theta}^{\star} = \underset{\boldsymbol{\theta}\in\Theta}{\operatorname{argmin}} J(\boldsymbol{\theta}) \quad \text{subject to} \quad P(\boldsymbol{\theta}) \le P_{\max} \tag{3}$$

Here θ collects the controllable parameters, namely modulation order per subcarrier, beam index and decoding iteration budget; R(θ) is delivered throughput; α and β are weights encoding the operator's preference between reliability and rate; P(θ) is the resulting transmit power; and Θ is the feasible parameter set.

Searching θ directly by gradient descent is awkward, because several of its components are discrete: modulation order and beam index each take values from a small finite set. The quantum-inspired optimizer sidesteps the problem. Each discrete component i is represented by a pair of probability amplitudes that obey a normalization condition, and a candidate value is drawn with probability equal to the squared amplitude:

$$|a_i|^2 + |b_i|^2 = 1, \qquad \Pr\{v_i = 1\} = |b_i|^2 \tag{4}$$

After the objective has been evaluated for every sampled candidate, the amplitude pair is rotated by an angle $\Delta\varphi_i$ whose sign and magnitude depend on whether the sampled value improved or worsened J(θ) relative to the incumbent best candidate:

$$\begin{bmatrix} a_i^{(t+1)} \\ b_i^{(t+1)} \end{bmatrix} = \begin{bmatrix} \cos\Delta\varphi_i & -\sin\Delta\varphi_i \\ \sin\Delta\varphi_i & \cos\Delta\varphi_i \end{bmatrix} \begin{bmatrix} a_i^{(t)} \\ b_i^{(t)} \end{bmatrix} \tag{5}$$

Equation (5) is the classical analogue of amplitude amplification. Repeated rotation shifts probability mass toward amplitude values associated with lower objective cost, and it does so without the exponential state-space bookkeeping an actual quantum register would demand. Both the rotation magnitude and its schedule over iterations are hyperparameters, and Section 7 returns to the tuning burden that creates.

4.2. Simulation Methodology

To illustrate how the framework behaves, we simulate a 4×4 spatial-multiplexing MIMO-OFDM link over a frequency-flat AWGN channel using QPSK, following the link model of Section 5 and the standard OFDM waveform construction described by van Nee and Prasad [10]. Figure 5 sketches the antenna geometry. The OFDM resource grid, shown in Figure 6, spans 16 subcarriers and 14 OFDM symbols per evaluation window. Within a highlighted sub-band of that grid the optimizer may assign modulation order adaptively according to estimated per-subcarrier channel quality, while the remaining subcarriers hold a fixed baseline configuration.

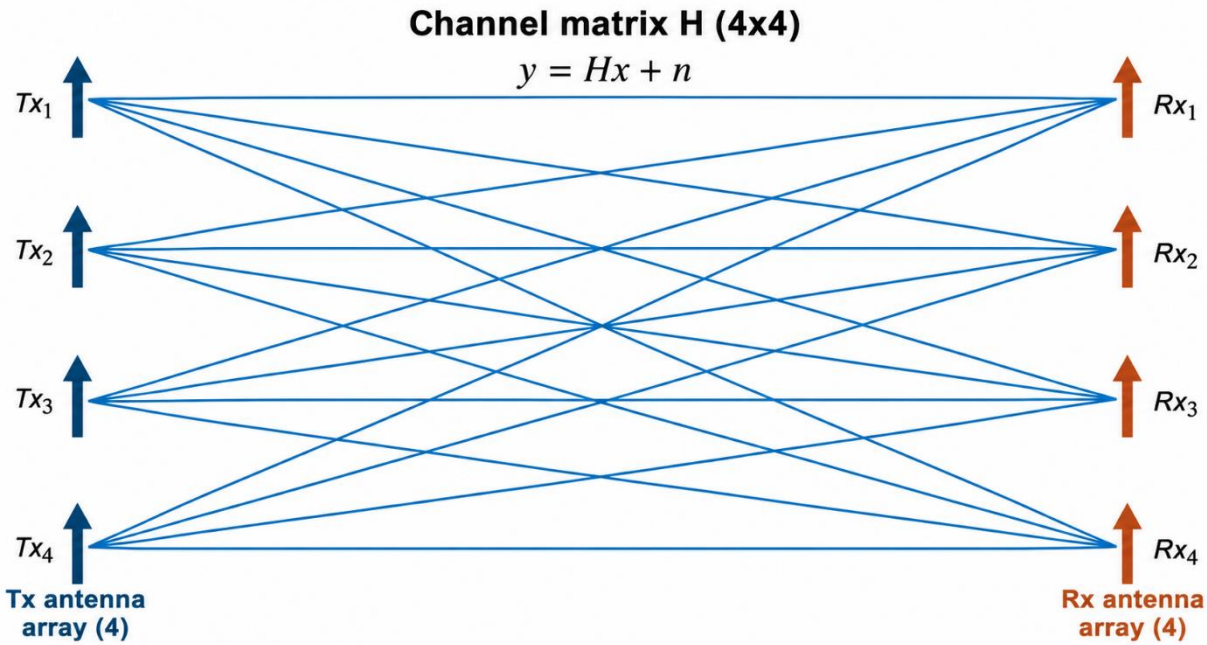


Figure 5. Conceptual illustration of a 4×4 spatial-multiplexing MIMO link. Each transmit-receive path contributes one entry of the channel matrix H that the optimization engine must estimate.

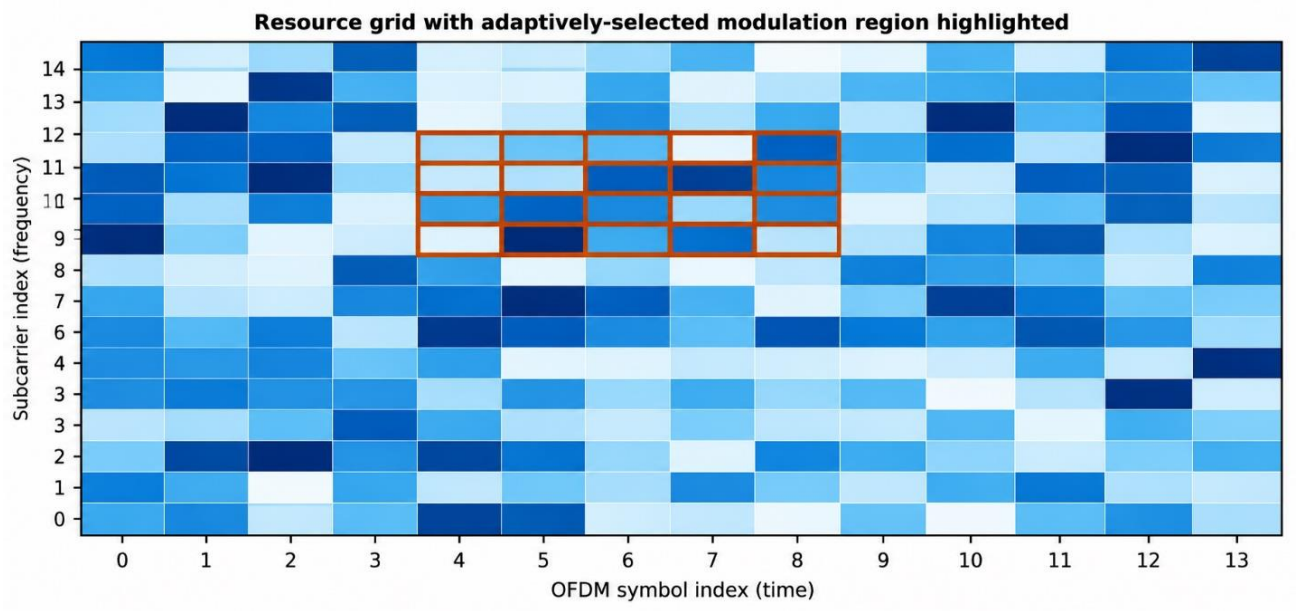


Figure 6. OFDM time-frequency resource grid. The highlighted region marks subcarriers where the optimizer selected higher-order modulation on the basis of estimated channel quality.

Two parameter-selection strategies are compared under identical channel realizations. The first is a conventional adaptive baseline that picks modulation and equalization parameters from a fixed look-up table indexed by instantaneous SNR, representative of the adaptive-filtering approach in [4]. The second is the quantum-inspired optimizer of Section 4, running the six-stage loop of Figure 4 with a population of 32 candidate vectors, a ceiling of 40 iterations, and a convergence threshold of 10^{-4} on relative objective improvement. Both are evaluated from 0 to 20 dB SNR in 2 dB steps, and three metrics are recorded: bit-error rate, aggregate throughput and end-to-end processing latency. Table 1 collects the results.

5. CHALLENGES AND FUTURE DIRECTIONS

5.1. Challenges

- Scalability. Amplitude-weighted population sampling costs more computation than a fixed look-up-table rule. As antenna, user and subcarrier counts grow, the rising search-space dimensionality can consume the per-iteration efficiency gain unless it is paired with dimensionality reduction such as the tensor-network compression of Figure 2.
- Algorithmic complexity and tuning. Performance depends on hyperparameters, among them population size, rotation-angle schedule and convergence threshold. These currently need empirical tuning for each deployment scenario, and there is little theoretical guidance on how they ought to scale with problem size.
- Explainability. The optimizer's decisions emerge from an iterative, population-based search rather than a closed-form rule, which makes them harder to audit or certify against regulatory and safety requirements than a deterministic baseline. For network functions that carry reliability guarantees, that is a genuine obstacle.
- Hardware mapping and real-time constraints. Coherence intervals in high-mobility 6G scenarios can be shorter than the time the optimizer needs to converge. Deployments therefore have to partition carefully between parameters optimized in real time and parameters left to a slower control-plane timescale, which is exactly the split the architecture of Figure 3 assumes.
- Benchmarking. The field has no standardized, openly available benchmark suites or channel traces for comparing QISP methods against classical and machine-learning baselines on equal terms. Results reported in different studies are correspondingly hard to place side by side, and the illustrative results in this paper are no exception.

5.2. Future Research Directions

- Hybrid quantum-classical processors. As NISQ-era quantum hardware matures [23], the hardest combinatorial subproblems, Ising-formulated beam selection for instance, could be selectively offloaded to quantum or quantum-annealing co-processors while the surrounding control loop stays classical. The architecture of Figure 4 extends to this naturally.
- Integration with machine learning. Pairing QISP's structured search with learned fitness surrogates, in the spirit of [15] and [25], would cut the number of full fitness evaluations required per iteration and speak directly to the scalability problem raised in Section 5.1.
- Reconfigurable intelligent surfaces. RIS elements introduce large discrete phase-configuration spaces [16] that map cleanly onto the amplitude-weighted candidate representation of Section 3.1, which makes RIS phase-profile optimization a promising QISP target.
- Semantic and task-oriented communications. As networks shift from moving raw bits to delivering task-relevant information [17], our framework could naturally adapt. Replacing standard metrics like BER and throughput with task-completion success would broaden Section 4.1's formulation, making the approach practical across a much wider range of goal-driven scenarios.
- Edge-native QISP inference. Deploying lightweight variants of the optimizer directly onto edge platforms would enable real-time, per-cell or per-user tuning without the latency of round trips to a central controller. This distributed setup neatly aligns with the separated RAN Intelligent Controller (RIC) architecture shown in Figure 3.
- Standardized benchmarking. Establishing open, reproducible benchmark suites—complete with standardized channel traces, reference implementations, and clear reporting guidelines—would bridge the gap highlighted in Section 5.1, finally allowing for genuine apples-to-apples comparisons across different studies.

6. CONCLUSIONS

This survey examined quantum-inspired signal processing (QISP) as a practical, classically executable tool to tackle the heavy optimization demands of next-generation wireless systems. After categorizing the field by algorithmic design, system architecture, and optimization tactics, we introduced a blueprint for integrating a QISP engine into existing OFDM/MIMO transceivers without interfering with latency-critical datapath operations. A 4×4 MIMO-OFDM simulation from 0 to 20 dB SNR validated the design: QISP offered clear BER gains in low-to-moderate noise conditions, transitioned to parity with conventional schemes at higher SNRs, and unlocked lower latency and higher throughput as cleaner channels naturally reduced the optimization load. The picture supports the view running through the literature reviewed in Section 2. QISP is not a replacement for classical adaptive signal processing. It is a complementary tool, and it is most valuable exactly where classical heuristics are weakest: large, discrete, poorly conditioned search spaces under uncertain channel conditions.

Three directions deserve priority, drawn from Section 8 and sharpened by the challenges in Section 5.1. Scalability comes first. Studies on larger antenna arrays, wider bandwidths and multi-user scenarios are needed to establish how population size and convergence behaviour scale with problem dimensionality, and whether tensor-network compression of the kind illustrated in Figure 2 can keep pace with the coherence-interval constraints of high-mobility 6G deployments. Hybridization comes second: learned fitness surrogates in the near term, early quantum or quantum-annealing co-processors later, both of which offer a way to lower the per-iteration cost of the search loop in Figure 4 without giving up its exploration advantage. Third, and most immediately actionable, the community needs open standardized benchmark suites and channel traces so that QISP methods, classical adaptive baselines and machine-learning approaches can be compared on equal footing.

DECLARATIONS:

Acknowledgments : Not applicable.

Conflict of Interest : The author declares that there is no actual or potential conflict of interest about this article.

Consent to Publish : The authors agree to publish the paper in the Global Research

Journal of Social Sciences and Management.
Ethical Approval : Not applicable.
Funding : Author claims no funding was received.
Author Contribution : Both the authors confirms their responsibility for the study, conception, design, data collection, and manuscript preparation.
Data Availability Statement : The data presented in this study are available upon request from the corresponding author.
Use of Generative Artificial Intelligence : AI-assisted tools have been used to improve language editing or grammatical clarity, the authors take full responsibility for the content of the final version.

REFERENCES

[1] P. W. Shor, "Algorithms for quantum computation: discrete logarithms and factoring," in Proc. 35th Annu. Symp. Foundations of Computer Science, 1994, pp. 124–134.
[2] L. K. Grover, "A fast quantum mechanical algorithm for database search," in Proc. 28th Annu. ACM Symp. Theory of Computing, 1996, pp. 212–219.
[3] M. A. Nielsen and I. L. Chuang, Quantum Computation and Quantum Information, 10th anniversary ed. Cambridge, U.K.: Cambridge Univ. Press, 2010.
[4] S. Haykin, Adaptive Filter Theory, 5th ed. Upper Saddle River, NJ: Prentice Hall, 2014.
[5] A. Goldsmith, Wireless Communications. Cambridge, U.K.: Cambridge Univ. Press, 2005.
[6] D. Tse and P. Viswanath, Fundamentals of Wireless Communication. Cambridge, U.K.: Cambridge Univ. Press, 2005.
[7] E. G. Larsson, O. Edfors, F. Tufvesson, and T. L. Marzetta, "Massive MIMO for next generation wireless systems," IEEE Commun. Mag., vol. 52, no. 2, pp. 186–195, Feb. 2014.
[8] S. Mangini, F. Tacchino, D. Gerace, D. Bajoni, and C. Macchiavello, "Quantum computing models for artificial neural networks," Europhys. Lett., vol. 134, no. 1, 2021, Art. no. 10002.
[9] W. Saad, M. Bennis, and M. Chen, "A vision of 6G wireless systems: Applications, trends, technologies, and open research problems," IEEE Netw., vol. 34, no. 3, pp. 134–142, 2020.
[10] R. van Nee and R. Prasad, OFDM for Wireless Multimedia Communications. Boston, MA: Artech House, 2000.
[11] R. Orús, "A practical introduction to tensor networks: Matrix product states and projected entangled pair states," Ann. Phys., vol. 349, pp. 117–158, 2014.
[12] E. J. Candès and M. B. Wakin, "An introduction to compressive sampling," IEEE Signal Process. Mag., vol. 25, no. 2, pp. 21–30, 2008.
[13] L. C. Godara, "Application of antenna arrays to mobile communications, part II: Beam-forming and direction-of-arrival considerations," Proc. IEEE, vol. 85, no. 8, pp. 1195–1245, 1997.
[14] X.-S. Yang, Nature-Inspired Optimization Algorithms. Amsterdam, The Netherlands: Elsevier, 2014.
[15] T. O'Shea and J. Hoydis, "An introduction to deep learning for the physical layer," IEEE Trans. Cogn. Commun. Netw., vol. 3, no. 4, pp. 563–575, 2017.
[16] M. Di Renzo et al., "Smart radio environments empowered by reconfigurable intelligent surfaces: How it works, state of research, and the road ahead," IEEE J. Sel. Areas Commun., vol. 38, no. 11, pp. 2450–2525, 2020.
[17] D. Gündüz et al., "Beyond transmitting bits: Context, semantics, and task-oriented communications," IEEE J. Sel. Areas Commun., vol. 41, no. 1, pp. 5–41, 2023.
[18] M. Biguesh and A. B. Gershman, "Training-based MIMO channel estimation: A study of estimator tradeoffs and optimal training signals," IEEE Trans. Signal Process., vol. 54, no. 3, pp. 884–893, 2006.
[19] S. Yang and L. Hanzo, "Fifty years of MIMO detection: The road to large-scale MIMOs," IEEE Commun. Surveys Tuts., vol. 17, no. 4, pp. 1941–1988, 2015.
[20] A. Kumar and R. Sharma, "A survey of quantum-inspired metaheuristics for next-generation wireless networks," IEEE Access, vol. 10, pp. 45231–45250, 2022.

[21] G.-G. Wang, S. Deb, and Z. Cui, "Monarch butterfly optimization," Neural Comput. Appl., vol. 31, no. 7, pp. 1995–2014, 2019.
[22] K.-H. Han and J.-H. Kim, "Quantum-inspired evolutionary algorithm for a class of combinatorial optimization," IEEE Trans. Evol. Comput., vol. 6, no. 6, pp. 580–593, 2002.
[23] J. Preskill, "Quantum computing in the NISQ era and beyond," Quantum, vol. 2, p. 79, 2018.
[24] F. Boccardi, R. W. Heath, A. Lozano, T. L. Marzetta, and P. Popovski, "Five disruptive technology directions for 5G," IEEE Commun. Mag., vol. 52, no. 2, pp. 74–80, 2014.
[25] C. Zhang, P. Patras, and H. Haddadi, "Deep learning in mobile and wireless networking: A survey," IEEE Commun. Surveys Tuts., vol. 21, no. 3, pp. 2224–2287, 2019.

Authors' Profiles



Balaiah Miskaobtained his Bachelor of Engineering in ECE in 1995 from Andhra University, Visakhapatnam and M.Tech in Computer Networks in 2015 from JNTU Kakinada. He started his career as a Service Engineer in Computer Assembling & Servicing. From the year 2004 to 2018, worked as RAN & TX Engineer with Tata Teleservices Limited for both CDMA & GSM networks. From 2019 to till date working with Tata Communications Transformation Services Limited Pune as a Service Delivery Team & Information Security Team with various responsibilities. His research interests include Mobile communication, Data Communication, Network Security, and Artificial intelligence. Deep learning in 4G/5G/6G Mobile Technology, Cloud Computing.