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Fuzzy Topological Graph Neural Networks for Modeling Nonlinear Quantum Systems under High-Dimensional Uncertainty

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Abstract

The dimensions of the state space of a nonlinearity in quantum system and the uncertainty in the interaction between the coupled variables make it more challenging to model such systems. Traditional neural networks and graph-learning algorithms are capable of modeling complicated nonlinear relationships, but tend to suffer a drop in performance in the presence of uncertain or harmful perturbations. This paper introduces a Fuzzy Topological Graph Neural Network (FT-GNN) in the strong modeling of nonlinear quantum systems in high-dimensional uncertainty. The fuzzy membership functions are used to describe the uncertain quantum-state variables to support ambiguity and perturbation of the state space. Only a fuzzy topological graph is then built to capture nonlinear dependencies and similarity relationships between the state dimensions. Topology-conscious graph neural propagation is used to learn the structured nonlinear representations of the resulting graph. To enhance robustness, a minimax optimization scheme is incorporated in the learning scheme, which minimizes model loss on worst-case perturbations in a bounded uncertainty set. The computational experiments are performed on various levels of uncertainty and compared to the traditional neural and graph-based models. Root means square error (RMSE), coefficient of determination (R^2), Macro-F1 score, worst-case loss (WCL), and robustness retention (RR) are used to evaluate the performance. The quantitative data show better predictive fidelity, consistency in classification, reduced worst-case loss, and better performance retention as uncertainty increases, which validate FT-GNN as a powerful computational framework to model nonlinear quantum-systems.

Keywords: Fuzzy topology; graph neural network; nonlinear quantum systems; high-dimensional uncertainty; minimax optimization; robust learning.

1. Introduction

High-dimensionality in the state space, a strong interaction between the state variables, and the complexity of the dynamical behaviourcharacterise nonlinear quantum systems. The dependency on nonlinear relationships between state variables enables small changes in state variables to be propagated as the system dimensionality increases, and to significantly change the resulting system response. Besides this, mathematical modeling becomes challenging to rely on due to uncertainty caused by state representation, change in parameters and

perturbations. In these environments, conventional analysis models can be computationally constrained, and generic machine-learning algorithms can be able to learn nonlinear maps without explicit structural relationships between the interacting dimensions.

Fuzzy modeling is a valuable mathematical tool to model uncertain or imprecise states by using graded membership as opposed to strict numerical boundaries. Graph-based representations also allow the dimensions of the system to be represented as nodes that are connected by weighted edges, which can represent nonlinear dependencies between them. Graph neural networks (GNNs) are therefore able to learn representations by combining information by such dependencies. But the accuracy of prediction in the nominal conditions is not sufficient in case of uncertain quantum systems since representations learned through learning can degrade in case there are high-dimensional perturbations to multiple interacting states at the same time.

The resistance to these perturbations demands an optimization principle to be robust against undesired uncertainty configurations. Optimization Maximax optimization offers this functionality, minimizing the loss to the worst admissible perturbation of a given uncertainty set. Although advances have been made in the area of fuzzy modeling, graph learning, and robust optimization, they are usually studied separately. There is still, thus, a gap to a single mathematical model capable of all at once modeling fuzzy state uncertainty, topological dependencies, nonlinear graph interactions and worst-case high-dimensional perturbations. This is a gap to which is especially applicable when robustness is to be considered in terms of the predictive performance and the worst-case behavior.

This paper overcomes this shortcoming by designing a Fuzzy Topological Graph Neural Network (FT-GNN) with minimax optimization to model nonlinear quantum-systems. The most impactful contributions include the development of a high-dimensional nonlinear quantum-state model with bounded uncertainty; a fuzzy representation of uncertain states and topology-aware representation of their nonlinear interactions; graph neural learning to extract structured system representations; and a minimax model that trains the FT-GNN to the worst-case admissible perturbations. The resultant framework is assessed computationally by the use of RMSE, (R^2), Macro-F 1, worst-case loss (WCL) and robustness retention (RR) which give complementary data on modeling fidelity, pattern-recognition capacity, and robustness to more uncertainty.

2. Related Work

High-dimensional and nonlinear systems demand computational models that have the ability to model the complex interactions, whilst being stable under conditions of uncertainty. The computational complexity has been solved by high-dimensional numerical modeling, and optimization of complex nonlinear systems, signal-processing problems, and challenging computational optimization problems, have effectively been optimized by predictive learning, and quantum-inspired methods, respectively [11], [8], and [10]. Such studies are helpful to offer background, yet as dimensionality grows, uncertainty and structural effects are problematic.

Graph based learning offers a good mechanism through which one can represent interplay between coupled variables. Topological GNNs use higher-order structural information [1], geometric deep learning extends learning to non-Euclidean spaces [3], and graph/manifold convolution facilitates structured nonlinear feature extraction [4]. Fuzzy neural models offer adaptive processing of the uncertain high-dimensional data [2], and fuzzy GNNs incorporate graded uncertainty in the graph learning [13]. The combination of fuzzy representation and topology-aware learning is supported by these developments in dealing with the uncertain nonlinear systems.

Other developments have included quantum-oriented graph learning with quantum GNNs [5], quantum positional graph encodings [6], quantum-inspired hierarchical neural representations [7] and quantum graph convolution [14]. The quantum-inspired GNN optimization also indicates the notion of interaction between graph learning and quantum optimization [15], whereas graph-learning architectures that are not all hybrid can also reflect the greater potential of structured learning robustness [12]. Together, these methods suggest that graph-based and quantum-inspired representations are capable of representing intricate dependencies that might be missed by conventional learning methods using vectors.

Although these advances exist, there is a definite gap in research. The current literature is mainly focused on topological learning, fuzzy high-dimensional modeling, geometric graph learning, [4], [6], and quantum graph representations, quantum-inspired learning, and optimization, predictive and signal-processing applications, high-dimensional computation, hybrid graph learning, and fuzzy GNNs, respectively. An integrated system that integrates fuzzy uncertainty representation, topological dependency modeling, nonlinear GNN learning, high-

dimensional perturbation analysis, and minimax worst-case optimization has not been well investigated. The proposed FT-GNN fills this gap with a single strong mathematical model that includes these aspects.

3. Methodology

The suggested Fuzzy Topological Graph Neural Network (FT-GNN) combines the concepts of nonlinear quantum-state modeling, fuzzy uncertainty representation, topology-conscious graph learning and minimax optimization into the common computational framework. The first methodology develops the evolution of a high-dimensional nonlinear quantum system and adds bounded perturbations as a way to reflect uncertainty. These uncertain states are then converted to fuzzy representations and structured in the form of a weighted topological graph. Graph neural propagation is an algorithm that learns the nonlinear relationships in this representation, and minimax optimization enhances robustness to worst-case perturbations. Computational experiments are then used to assess nominal modeling performance, and robustness to incremental uncertainty.

3.1 Nonlinear Quantum System and Uncertainty Modeling on a High-Dimensional Level.

Consider a nonlinear quantum system represented by a d-dimensional state vector containing the system variables at discrete time t. The state is expressed as

$$x(t) = [x_1(t), x_2(t), \dots, x_d(t)]^T. \quad (1)$$

The temporal evolution of the system is modeled through a nonlinear state-transition function as

$$x(t+1) = x(t) + \Delta t F(x(t), u(t)) + \epsilon(t), \quad (2)$$

where Δt denotes the discrete evolution interval, $F(\cdot)$ characterizes nonlinear coupling among the state dimensions, $u(t)$ represents external or control influences, and $\epsilon(t)$ accounts for stochastic modeling variations. The nonlinear mapping itself allows interactions between a variety of state dimensions, instead of independent or linear evolution.

To investigate robustness, the nominal state is subjected to a high-dimensional perturbation vector δ. The uncertain state and its admissible uncertainty region are defined as

$$\tilde{x} = x + \delta, \qquad \delta \in U = \{\delta : \| \delta \|_p \leq \varepsilon\}, \quad (3)$$

In which ε is the radius of uncertainty and the p-norm is the collective perturbation across dimensions. Computational uncertainty levels of 0%,5%,10%,15%, and 20% are considered, ranging from the nominal condition to increasingly adverse perturbations. With this formulation, one can systematically study whether or not the learned quantum-state representation can continue to be trusted as uncertainty propagates into the nonlinear coupled dimensions.

3.2 Fuzzy Topological Graph Representation

Direct numerical states may be sensitive to perturbations near decision or structural boundaries. Therefore, each uncertain state dimension is transformed into fuzzy information using Gaussian membership functions corresponding to Low (L), Medium (M), and High (H) states:

$$\mu_{ikr} = exp\left[-\frac{(\tilde{x}_{ik} - c_r)^2}{2s_r^2}\right], \qquad r \in \{L, M, H\}, \quad (4)$$

where μ_{ikr} represents the membership degree of the k-th dimension of sample i in fuzzy state r, while c_r and s_r denote its center and spread, respectively. This representation retains gradual transitions between uncertain states instead of assigning them to rigid boundaries.

The fuzzy information is subsequently organized into a topological graph $G = (V, E, A, F)$, where V denotes state-dimension nodes, E represents their dependency relationships, F contains fuzzy node features, and A is the weighted adjacency matrix. The strength of the relationship between nodes j and k is defined as

$$A_{jk} = | \rho_{jk} | exp\left[-\frac{\| f_j - f_k \|_2^2}{2\sigma_g^2}\right], \quad (5)$$

where $|\rho_{jk}|$ represents dependency strength, f_j and f_k are fuzzy feature vectors, and σ_g controls sensitivity to fuzzy-feature distance. Accordingly, a good graph relationship must have high dependency, as well as, similarity in fuzzy state features. Fig. 1 depicts this fuzzy topological representation, where the dimensions of quantum-state spaces represent the graph nodes, fuzzy memberships define the information of the graph node and the weighted connections maintain the nonlinear relationships between the nodes in the face of uncertainty.

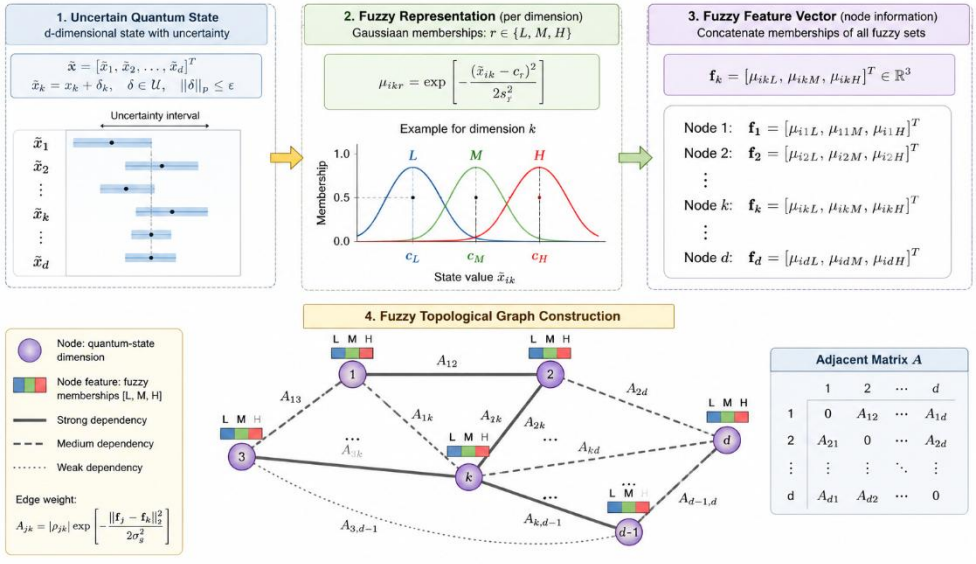


Fig. 1. Fuzzy Topological Graph Representation of Uncertain Quantum States

3.3 Topology-Aware Graph Learning and Minimax Optimization

The resulting fuzzy topological graph is processed using graph neural propagation to capture higher-order interactions among interconnected quantum-state dimensions. At graph layer l, the node representation is updated according to

$$H^{(l+1)} = \phi(\hat{A}H^{(l)}W^{(l)} + b^{(l)}), _____(6)$$

where $\hat{A}$ denotes the normalized fuzzy topological adjacency matrix, $H^{(l)}$ contains node representations, $W^{(l)}$ and $b^{(l)}$ are trainable parameters, and $\phi(\cdot)$ denotes the nonlinear activation function. The successive propagation thus integrates fuzzy information within a locality with dependency structures which are acquired on the surrounding dimensions of state.

The resulting aggregate node representations are computed with dimension-specific importance coefficients to create a system-level representation and a system-level prediction:

$$z = \sum_{j=1}^{d} \alpha_j h_j^{(L)}, \qquad \hat{y} = f_\theta(z), _____(7)$$

where α_j determines the contribution of state dimension j, $h_j^{(L)}$ is its final graph representation, and $f_\theta(.)$ denotes the prediction mapping. For pattern-recognition analysis, the predicted states are categorized into stable, transitional, and complex/unstable conditions.

Robustness is incorporated directly into parameter learning rather than being evaluated only after training. The central minimax formulation is

$$\min_{\theta} \max_{\delta \in U} L\big(f_\theta\big(G(x+\delta)\big), y\big) _____ (8)$$

where the inner maximization identifies an admissible perturbation that maximizes the model loss, while the outer minimization updates θ to reduce this worst-case response. In this way, the model will make optimal use of parameters, rather than optimising the average nominal performance, resistant to undesirable high-dimensional perturbations. The entire FT-GNN pipeline, as summed up in Fig. 2, is a set of uncertain quantum-

state inputs, fuzzy transformation, topological graph construction, graph representation learning, prediction, and inner-max/outer-min optimization cycle.

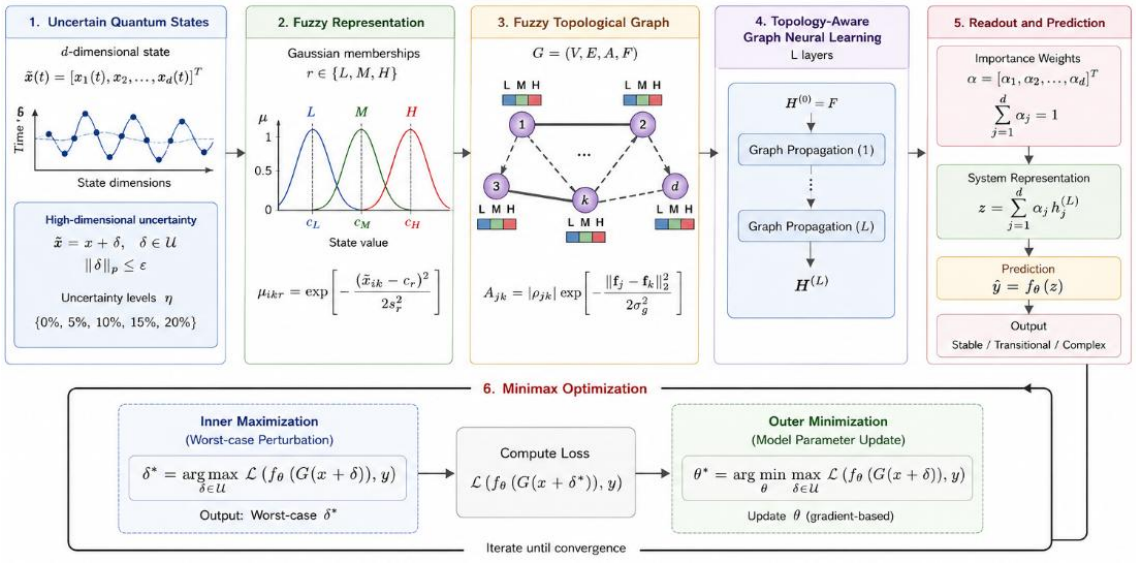


Fig. 2. Proposed FT-GNN with Minimax Optimization Framework

3.4 Computational Setup and Performance Evaluation

The computational analysis takes into account high-dimensional nonlinear state sequences created with the help of the suggested system model. The number of computational samples is 10,000 with 50 dimensions of states and uncertainty is gradually added (at 0, 5, 10, 15, and 20 percent). The samples are split into four sections 70% training, 15% validation, and 15% testing, and all these proportions are retained in all the comparative methods. There are three Gaussian fuzzy states, Low, Medium and High, which have centers of 0.20, 0.50 and 0.80 and a spread of 0.15. The FT-GNN is composed of two graph-learning layers with 64 and 32 hidden units with ReLU activation. The Adam optimizer is used with a learning rate of 0.001, a batch size of 64 and 200 epochs in training. Ten consecutive runs are conducted in the same conditions of the experiment. To evaluate the effect of fuzzy representation, topological learning, and worst-case robust optimization, the proposed Minimax FT-GNN is compared with MLP, standard GNN, Fuzzy GNN, and FT-GNN without the minimax optimization.

To provide a comparative analysis, an MLP as a non-graph baseline, a regular GNN to learn the structure, a Fuzzy GNN to learn the structure with uncertainty concerns, an FT-GNN without minimax optimization to isolate the influence of topological representation, and the proposed minimax-optimized FT-GNN are used. All models are tested under the same nominal and perturbed conditions to ensure that the results are improved because of fuzzy topology and worst-case optimization as opposed to variation in experimental setup.

There are five measurement complements that are used to measure nonlinear prediction, pattern recognition, and uncertainty robustness. Their combined assessed set is given as

$$M = \{RMSE \downarrow, R^2 \uparrow, Macro - F1 \uparrow, WCL \downarrow, RR \uparrow\}, \qquad WCL = \max_{\delta \in U} L_\delta, RR(\eta) = \frac{P_\eta}{P_0} \times 100\%. _____(9)$$

RMSE measures nonlinear state-prediction error, while R^2evaluates the fidelity with which the model reproduces state variation. Macro-F1 is a method of offering class-balanced evaluation of quantum-state pattern recognition. The WCL is an approach which directly measures the minimax objective by measuring the maximum loss experienced in the prescribed uncertainty set. RR is a measure of the percentage of nominal result retained at a level of uncertainty of η. These metrics combined allow distinguishing between traditional predictive performance and the capability of the offered FT-GNN to maintain reliable behavior even in the presence of unfavorable high-dimensional uncertainty.

5. Results and Discussion

5.1 Overall Comparative Performance

The comparison findings indicate a steady decline between the traditional MLP to the suggested Minimax FT-GNN. The MLP achieves an RMSE of 0.091, R^2 of 0.872, Macro-F1 of 0.806, WCL of 0.238, and RR of 78.4%, whereas the standard GNN improves these values to 0.073, 0.907, 0.851, 0.194, and 82.7%, respectively. The addition of fuzzy representation increases the Fuzzy GNN to an RMSE of 0.061, R 2 of 0.929, Macro-F1 of 0.889, WCL of 0.157 and RR of 86.5%. The FT-GNN without minimax optimization reaches 0.052, 0.946, 0.918, 0.131, and 88.9%, respectively. The best overall performance is offered by the proposed Minimax FT-GNN with the lowest RMSE 0.041, R 2 0.963, Macro-F1 0.942, WCL 0.096 and RR 92.8 percentage. The difference between nominal prediction and classification performance to much more robust worst-cases is summarized in Table 1.

Table 1. Comparative Performance of Baseline and Proposed Models

Model	RMSE ↓	R^2 ↑	Macro-F1 ↑	WCL ↓	RR (%) ↑
MLP	0.091	0.872	0.806	0.238	78.4
Standard GNN	0.073	0.907	0.851	0.194	82.7
Fuzzy GNN	0.061	0.929	0.889	0.157	86.5
FT-GNN without Minimax	0.052	0.946	0.918	0.131	88.9
Proposed Minimax FT-GNN	0.041	0.963	0.942	0.096	92.8

5.2 Performance under Increasing High-Dimensional Uncertainty

A transition in the uncertainty between 0% and 20% makes performance drop in all of the considered models, yet the suggested Minimax FT-GNN is significantly more resilient. Its RMSE increases only from 0.036 to 0.049, while R^2 decreases from 0.972 to 0.951 and Macro-F1 from 0.953 to 0.921. The retention of robustness is still at 90% in the most uncertain situation and indicates that the majority of the nominal performance is retained. Conversely, MLP, standard GNN and non-minimax variants deteriorate more with increases in perturbation severity. Fig. 3 shows the change in performance over this time and validates the fact that minimax optimization constrains uncertainty-based degradation over the high-dimensional conditions studied.

5.3 Worst-Case Minimax Analysis

The proposed Minimax FT-GNN has controlled degradation with the increasing uncertainty in high-dimensional data as shown in Fig. 3. At uncertainty levels of 0%, 5%, 10%, 15%, and 20%, WCL increases gradually from 0.061, 0.070, 0.081, 0.093, to 0.108, respectively, while RR decreases moderately from 100.0%, 98.1%, 96.4%, 94.5%, to 92.8%. Throughout the entire range of uncertainty, there is only an increment in WCL of 0.047, and the decline in RR at 7.2 percentage points. This 92.8% performance retention with uncertainty of 20% suggests that the minimax strategy successfully bounds the worst-case performance degradation and offers consistent FT-GNN behaviour with more and more negative perturbations.

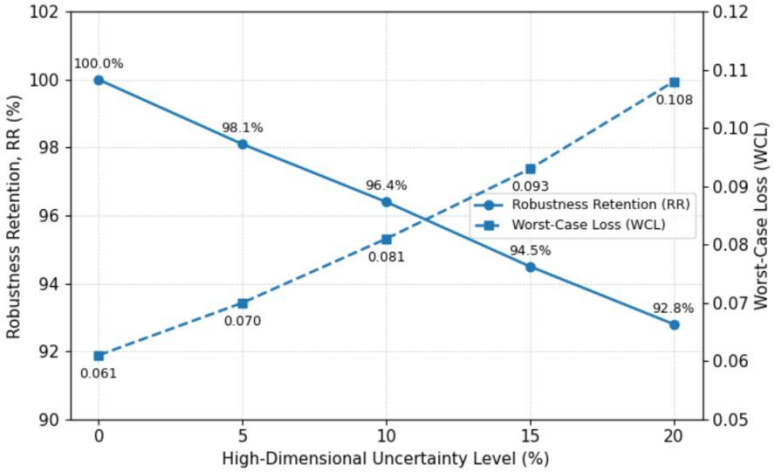


Fig. 3. Robustness and Worst-Case Performance under Increasing High-Dimensional Uncertainty

5.4 Fuzzy Topological Representation Analysis

The fuzzy topological representation enhances performance by maintaining nonlinear relationships and minimizing the sensitivity to uncertainties in states. Topology-conscious weighting focuses on structurally

significant interactions between interacting dimensions and Fuzzy memberships give descriptive accounts of state conditions gradual, and small perturbations of state do not create sudden changes in the description. This can be observed in the change in the typical GNN of RMSE of 0.073 and Macro-F1 of 0.851 to the FT-GNN of RMSE of 0.052 and Macro-F1 of 0.918 without minimax optimization. The respective decrease in WCL of 0.194 to 0.131 further shows that fuzzy topological modeling does not need the introduction of minimax optimization to increase the uncertainty tolerance.

5.5 Ablation and Sensitivity Analysis.

The ablation findings indicate the fact that all major components will play a part in the final performance. When the fuzzy representation is eliminated, RMSE goes up to 0.057 and WCL goes up to 0.149 with a decrease in the RR to 86.8%. When topological weighting is removed, the RMSE is 0.053, WCL=0.137 and RR=88.1%. Omission of minimax optimization produces an RMSE of 0.052, WCL of 0.131, and RR of 88.9%. In comparison, the complete model achieves an RMSE of 0.041, R^2 of 0.963, Macro-F1 of 0.942, WCL of 0.096, and RR of 92.8%. Table 2 thus validates the finding of complementary enhancements by fuzzy representation, topological weighting and minimax optimization, the latter having a notably significant effect on WCL and retention of robustness.

Table 2. Ablation Analysis of the Proposed FT-GNN

Model Variant	RMSE ↓	R^2 ↑	Macro-F1 ↑	WCL ↓	RR (%) ↑
Without Fuzzy Representation	0.057	0.938	0.902	0.149	86.8
Without Topological Weighting	0.053	0.943	0.911	0.137	88.1
Without Minimax Optimization	0.052	0.946	0.918	0.131	88.9
Full Minimax FT-GNN	0.041	0.963	0.942	0.096	92.8

5.6 Integrated Performance and Robustness Analysis

A combination of the results proves that the proposed Fuzzy Topological Graph Neural Network works best in Modeling Nonlinear Quantum Systems in High-Dimensional Uncertainty. Fuzzy uncertainty representation and topological dependency modelling enhance the maintenance of nonlinear dependencies between quantum-state dimensions, whereas graph-based learning support structure representation of nonlinear interactions. The increases in RMSE and R 2 are a measure of more nonlinear modeling accuracy, but the higher Macro-F1 is a measure of more consistent measurements of quantum-state patterns. The decreasing WCL exhibits better resistance to adverse perturbations, and the even greater RR is used to ensure that performance is less fragile to larger dimensional uncertainties. The results of the ablation also confirm that fuzzy representation and topological weighting increase structural stability whereas minimax optimization affords significant safeguarding against worst-case degradation. Nevertheless, the given results are obtained by the use of computationally generated nonlinear sequences of quantum states with limited uncertainty. Thus, they illustrate the mathematical and computational efficiency of the suggested approach instead of experimental verification, using measured quantum systems or physical quantum hardware.

6. Conclusion

The paper introduced a Fuzzy Topological Graph Neural Network (FT-GNN) with minimax optimization to characterize the nonlinear quantum systems in the high-dimensional uncertainty regime. It is based on a framework that integrates fuzzy representation of uncertain quantum states, fuzzy constructions of topological graphs to maintain nonlinear dependencies, and topology-aware GNN learning to represent structured states. Minimax optimization enhances further the robustness by ensuring that the model is less sensitive to the worst-case admissible perturbations. Computational findings showed that the suggested approach had an RMSE of 0.041, a R2 of 0.963, a Macro-F1 of 0.942, a WCL of 0.096, and a RR of 92.8% which is better than the tested baseline models in modeling fidelity and robustness. The uncertainty analysis also indicated that performance decreased to a controlled level (maximum 20% perturbation) which confirms the efficiency of the proposed worst-case optimization strategy. Nevertheless, the current results are restricted to nonlinear quantum states that are calculated by a computer and constrained on uncertainty. Future research will explore the theoretical convergence to minimum maxima, larger high-dimensional systems, and alternative uncertainty sets, real quantum-system measurements, and physical validation of quantum-hardware validation.

References

1. Horn, M., De Brouwer, E., Moor, M., Moreau, Y., Rieck, B., & Borgwardt, K. (2021). Topological graph neural networks. arXiv preprint arXiv:2102.07835.

2. Gu, X., Ni, Q., & Shen, Q. (2024). Multilayer evolving fuzzy neural networks with self-adaptive dimensionality compression for high-dimensional data classification. IEEE Transactions on Fuzzy Systems, 32(11), 6314-6328.

3. Bronstein, M. M., Bruna, J., Cohen, T., &Veličković, P. (2021). Geometric deep learning: Grids, groups, graphs, geodesics, and gauges. arXiv preprint arXiv:2104.13478.

4. Monti, F., Boscaini, D., Masci, J., Rodola, E., Svoboda, J., & Bronstein, M. M. (2017, July). Geometric deep learning on graphs and manifolds using mixture model cnns. In 2017 IEEE conference on computer vision and pattern recognition (CVPR) (pp. 5425-5434). IEEE.

5. Verdon, G., McCourt, T., Luzhnica, E., Singh, V., Leichenauer, S., &Hidary, J. (2019). Quantum graph neural networks. arXiv preprint arXiv:1909.12264.

6. Thabet, S., Djellabi, M., Sokolov, I., Kasture, S., Henry, L. P., & Henriet, L. (2024). Quantum positional encodings for graph neural networks. arXiv preprint arXiv:2406.06547.

7. Zhang, C., Su, Z., Li, Q., Song, D., & Tiwari, P. (2025). Quantum-inspired neural network with hierarchical entanglement embedding for matching. Neural Networks, 182, 106915.

8. Arvinth, N. (2025). AI-Driven Predictive Control and Optimization Framework for Renewable-Integrated Smart Power Grids. National Journal of Intelligent Power Systems and Technology, 34-41.

9. Hussai, M., & Getachew, B. (2025). Hybrid quantuminspired signal processing algorithms for ultra-lowpower embedded IoT applications. National Journal of Signal and Image Processing, 1(2), 10-18.

10. Barhani, D., & Kharabi, P. (2024). Accelerating NP-hard optimization via quantum-inspired classical algorithms. Journal of Reconfigurable Hardware Architectures and Embedded Systems, 1(1), 43-51.

11. Prabhakar, C. P., & Tamrakar, G. (2025). Advanced numerical techniques for solving high-dimensional integral equations in environmental engineering applications. Journal of Applied Mathematical Models in Engineering, 9-16.

12. Rahim, R. (2026). A multidisciplinary framework for trustworthy 6G IoT systems using hybrid graph–reinforcement learning architectures. Bridge: Journal of Multidisciplinary Explorations, 2(1), 26-32.

13. Wei, T., Hou, J., & Feng, R. (2020, July). Fuzzy graph neural network for few-shot learning. In 2020 International joint conference on neural networks (IJCNN) (pp. 1-8). IEEE.

14. Zheng, J., Gao, Q., &Lü, Y. (2021, July). Quantum graph convolutional neural networks. In 2021 40th Chinese Control Conference (CCC) (pp. 6335-6340). IEEE.

15. Jiang, L., Zhang, C., & Chen, F. (2025, August). QSeer: A Quantum-Inspired Graph Neural Network for Parameter Initialization in Quantum Approximate Optimization Algorithm Circuits. In 2025 IEEE International Conference on Quantum Computing and Engineering (QCE) (Vol. 1, pp. 1496-1504). IEEE.