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A Nonlinear Dimensional Analysis Framework Using Fuzzy Graph Theory and Deep Neural Networks for Quantum-Intelligent Systems

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Abstract
Nonlinear systems with high dimensions are highly challenging to model due to complex inter-dimensional interactions, imprecise measurements and time-varying interactions among system variables. Traditional non-linear learning techniques are usually applied in dimensions separately or on given representations, therefore are limited in uncertainty and varying relations structures. This paper provides the hypothesis of a nonlinear dimensional analysis framework to model the intelligent system robustly in quantum-inspired combining fuzzy graph theory with deep neural networks. The uncertain system states are described by using fuzzy representations and the weighted graph structure is utilized to represent nonlinear relationships between interacting dimensions. The dimension-aware deep graph learning mechanism learns adaptive weights of dimensions and obtains smaller nonlinear representations. Then, the learned features are converted by means of a pattern representation inspired by quantum computing for the purpose of distinguishing between stable, transitional and complex state of systems. The learning process is proposed to be a minimax optimization problem to increase the bounded perturbations' resistance whose loss is minimized jointly for the prediction and classification. Computational experiments with varying levels of uncertainties and dimensions are conducted to compare the proposed framework with the traditional neural as well as graph models. Root mean square error (RMSE), mean absolute error (MAE), coefficient of determination ((R^2)), classification accuracy and Macro F1-score are used to evaluate performance. Results have proved that the above framework can be applied accurately and uncertainty in intelligent high dimensional systems modeling and strong pattern identification with nonlinearity.

Keywords: Nonlinear dimensional analysis; fuzzy graph theory; deep neural networks; quantum-inspired intelligence; minimax optimization; nonlinear systems.

1. Introduction

The behavior of the system is computed by interacting variables of which many are nonlinear systems with high dimensions, such as intelligent control, complex networks, pattern recognition, and data-driven dynamical

modeling. These systems are hard to model due to nonlinear dependencies which can change across different dimensions and become more and more uncertain to perturbation. Conventional neural models are easily learnable by people, when the inter-dimensional relationships and uncertainty are explicitly defined in a vector form, they are often limited. This makes it difficult to continue to predict well and distinguish patterns with dimensionality and uncertainty as they continue to grow.

The fuzzy graph theory offers a practical way of overcoming these limitations to integrate these two elements of uncertainty representation and relational modeling. Fuzzy memberships can be used to represent the uncertainty of the state of a system while weighted graph relationships can be used to describe the relationships between the dimensions. These graph structures are useful for hierarchical abstraction of relational features of the nonlinear features when combined with a deep neural representation learning. The ability of dimension-aware learning to ignore less informative dimensions and to focus on informative dimensions also provides an improvement when trying to model high-dimensional complex states.

The idea of quantum-inspired intelligence provides one more description structure by amplitude- and phase-based descriptions of learned patterns, allowing to describe complex system states by a minimal probabilistic structure. But being correctly represented does not imply strength in cases where observations are subjected to uncertainty. The minimax optimization problem can solve this problem by maximizing the model parameters with respect to the admissible worst-case perturbations. Despite the fuzzy systems developed, the use of graph neural networks, deep learning, quantum-inspired computation and robust optimization applied in a combination to nonlinear dimensional modeling is limited. However, no work has been performed on exploring an integrated framework for fuzziness inter-dimensional connection, dimension-conscience deep learning, quantum inspired pattern recognition and minimax robustness.

To address this deficiency, this research paper proposes the nonlinear dimensional analysis using the fuzzy graph theory and deep neural networks of quantum-intelligent systems. The key results include uncertainty-aware fuzzy graphical modelling for capturing the nonlinear relationships among high-dimensional variables and dimension-aware deep-graph learning for capturing such nonlinear relationships that are informative. This is supported by a quantum-inspired representation to highlight stable, transitional and complex system patterns and minimax learning to increase robustness to small uncertainty. The computational assessment of the framework is performed by means of RMSE, MAE, R^{2} and classification accuracy and Macro F1-score in order to determine the performance of the nonlinear prediction and pattern-recognition.

2. Related Work

The parameters of high dimensional nonlinear systems demand strong representations in the encounter of extra interactions, redundant dimensions as well as computational complexity. Graphs based dimensional reduction keeps the discriminative structure [1] and adaptive fuzzy dimensional compression assists high dimensional classification [2]. Complex multidimensional engineering problems also have been solved using machine-learning optimization [3]. Moreover, the Type-2 fuzzy neural networks provide valuable representations of high dimensional data in a non-linear form [4] and the adaptive fuzzy-neural strategies are the extensions of the uncertainty-aware intelligent modeling [5]. The modeling of complex nonlinear systems is also efficient as evidenced by the existence of reduced order and AI-assisted computational methods [9], [10].

Relational dependencies and uncertainty may be expressed by both graph and fuzzy learning. On the other hand, Fuzzy graph neural networks combine graph propagation with fuzzy information [11] and robust fuzzy neural models can better infer in uncertain situation [14]. The interrelated representations in GNN networks have been successfully trained using message passing [12] and graph-processing networks have been demonstrated to be good for effective intelligent inference [7]. The methods, however, have little, if any, of the characteristics of dimensional explicitness and worst-case uncertainty treatment.

The learning process of quantum-inspired is a generalization of the traditional (probabilistic, amplitude, phase, complex-valued, tensor) representation of neural computation. Complex mathematical models can be learned with quantum-inspired tensor networks [6], complex convolutional architectures can be used to learn nonlinear feature representations [8], and quantum-inspired GNNs can be used to learn graphs plus quantum-inspired classification [13]. They are interesting concepts for modelling complex patterns and loosely related to the fuzzy dimensional modelling and minimax robustness.

The literature, however, has a lack of studies on the unified treatment of dimensional learning [1], [2], machine-learning optimization [3], fuzzy neural systems [4], [5], quantum-inspired learning [6], [8], [13] and graph processing [7], [11], [12] as well as nonlinear reduced-order modeling [9] and complex-system prediction [10] and robust fuzzy inference [14]. Existing strategies deal with these aspects to a great extent in isolation. This prompts a composite set up integrating nonlinear dimensional modeling, fuzzy graph representation, dimension

aware deep learning, quantum inspired pattern recognition, and minimax optimization towards precise and dependable learning as the dimensionality and uncertainty gain.

3. Hypothesized Nonlinear Dimensional Analysis Model.

The proposed scheme is suggested as a computational structure, which integrates a high-dimensional nonlinear non-linear data modeling, fuzzy graph constructions, dimension conscious deep graph learning, pattern representations inspired by quantum mechanics and minimax optimization. However, as demonstrated in Fig. 1, the uncertain nonlinear measurements are converted to fuzzy states and then the graph is constructed to represent the inter-dimensional relationships. Optimally identifying dimension-aware features is then achieved with the help of deep graph learning, where the importance of individual features is adaptively learned, and quantum-inspired encoding has been used as a compact code representation of the stable, transitional, and complex/unstable patterns of a system. Lastly, minimax learning is more resilient to bounded perturbation as well as learns together to predict nonlinear states and classify patterns.

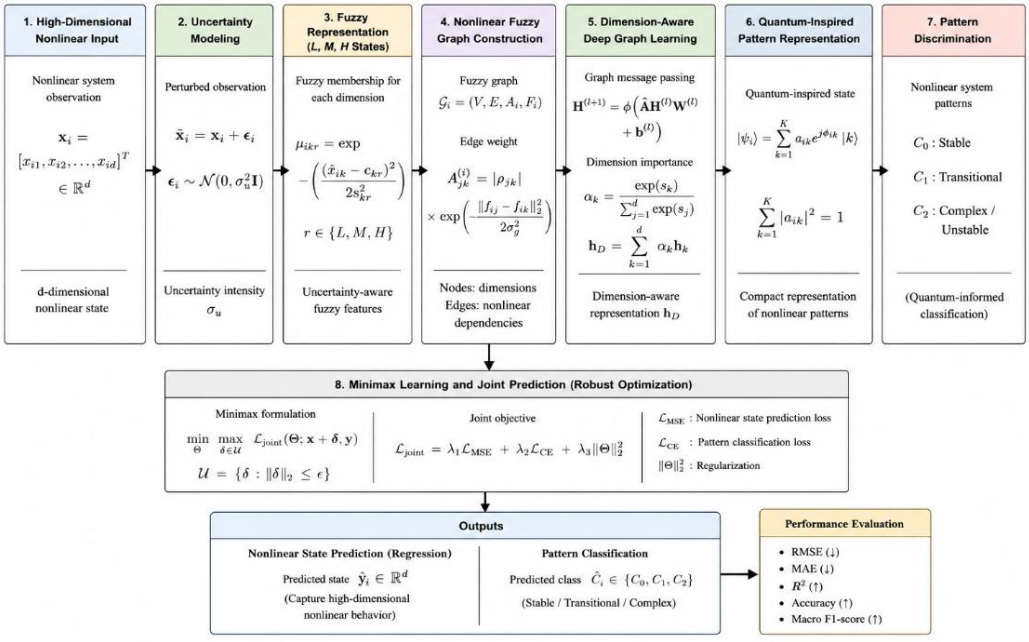


Fig. 1. Proposed nonlinear dimensional analysis framework.

3.1 High-Dimensional Nonlinear Data and Uncertainty Modeling

Graphic representations of uncertainty models for high dimensional nonlinear data.Graphic modeling of uncertainty models for high dimensional nonlinear data. A high dimensionality nonlinear system is represented as a vector of observations that has d interacting variables, where d is the dimensionality of the system, and each x_{ik}describes the state of the kth variable for observation i. The formulation does not make the assumption of independent dimensions; it could be nonlinear. Incorporating uncertainty, a zero-mean Gaussian noise is injected in the original observation: $\sigma_u$is the intensity of the uncertainty, and I is the identity matrix. The structure of the perturbed representation allows the framework to explore the nonlinear system behavior as conditions become increasingly uncertain.

$$x_i = [x_{i1}, x_{i2}, \ldots, x_{id}]T \in R_d. _____(1)$$

$$\tilde{x}_i = x_i + \epsilon_i, \qquad \epsilon_i \sim N(0, \sigma_u^2 I). _____(2)$$

3.2 Fuzzy Representation and Nonlinear Graph Construction

The uncertainty for each perturbed dimension is indicated using three fuzzy states of Low, Medium, and High, each of which has its associated center and spread represented by ckr and skr respectively. This fuzzy representation of features is placed in a graph where nodes represent the dimensions of the nonlinear systems and weighted edges represent their linkages. Adjacency strength is based on $|\ \rho jk\ |$and fuzzy-feature similarity; σg is the parameter that regulates the sensitivity of a graph. With this construction, the strongly related dimensions will share more information with each other in the subsequent graph learning process, while the weakly related dimensions will suppress the information flow.

$$\mu_{ikr} = exp\left[-\frac{(\tilde{x}_{ik} - c_{kr})^2}{2s_{kr}^2}\right], \qquad r \in \{L, M, H\}. _____(3)$$

$$G_i = (V, E, A_i, F_i). _____(4)$$

$$A_{jk}^{(i)} = \mid \rho_{jk} \mid exp\left(-\frac{\parallel f_{ij} - f_{ik} \parallel_2^2}{2\sigma_g^2}\right). _____(5)$$

3.3 Dimension-Aware Deep Graph Learning

The "fuzzy graph" is then propagated through deep layers and fused across dimensions to learn the relation features between the dimensions, which are nonlinear. A is the normalized adjacency matrix which controls information flow, $W^{(l)}, b^{(l)}$,and$\phi(\cdot)$introduce trainable transformation, bias, and nonlinear activation at layer l. All dimensions are not equal, so a softmax based weighting mechanism is used to learn an importance coefficient $\alpha_k$for each dimension, based on its learned score s_k. Using the weighted aggregation results in $h_D$which strengthens the informative dimensions' representation in the final nonlinear form.

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

$$\alpha k = \frac{exp(s_k)}{\sum_{j=1}^{d} exp(s_j)}, \qquad h_D = \sum_{k=1}^{d} \alpha_k h_k \,. _____(7)$$

3.4 Quantum-Inspired Pattern Representation

The dimension-aware nonlinear features are converted to a quantum-inspired state representation that is compact yet describes the complex system patterns. A probability of aik squared is associated with each basis state $\mid k\rangle$,with an amplitude aik and phase ϕik. The encoded representation can distinguish $C0$ stable, $C1$ transition and $C2$ complex/unstable state. This formulation is quantum-inspired, without assuming to execute on physical quantum hardware.

$$\mid \psi_i\rangle = \sum_{k=1}^{K} a_{ik} e^{j\phi_{ik}} \mid k\rangle, \qquad \sum_{k=1}^{K} \mid a_{ik} \mid^2 = 1 \,. _____(8)$$

3.5 Minimax Learning and Joint Prediction

A robust learning problem can be described as a minimax problem: The inner optimisation task is to find an adverse perturbation in the bounded uncertainty set U; the outer one is to try and minimise the worst-case loss for the selected Θ. The uncertainty magnitude is admissible depending on the perturbation radius ϵ. The state prediction and pattern classification losses, namely mean squared-error loss and cross-entropy loss are jointly optimized with an L_2regularization term that controls the size of the model. These goals are struck off with three parameters: the $\lambda_i$values, which balance these goals so that the framework learns predictive and discriminative nonlinear representations without being overly sensitive to bounded uncertainty.

$$\min_{\Theta} \max_{\delta \in U} L_{joint}(\Theta; x + \delta, y), \qquad U = \{\delta : \parallel \delta \parallel_2 \leq \epsilon\}. _____(9)$$

$$L_{joint} = \lambda_1 L_{MSE} + \lambda_2 L_{CE} + \lambda_3 \parallel \Theta \parallel_2^2 \,. _____(10)$$

4. Experimental Setup and Performance Metrics

4.1 Computational System and Simulation Configuration

The proposed framework is tested on a computationally-generated nonlinear system with 10,000 observations. Different dimensional systems have been tested at 5, 10, 20, 30 and 50 dimensions and nonlinear coupling coefficients have been tested at 0.05, 0.10, 0.20, 0.30 and 0.40, thus yielding different interaction strengths. There are also four rounds of uncertainty (0%, 5%, 10%, 15% and 20%) to study the robustness of the solution for increasingly mismatched scenarios. The observations created are split into 70% training, 15% validation and 15% testing subsets. The dimension-aware graph model includes two graph-learning layers, is (hyper-)parameterized with a learning rate of 0.001 and a batch size of 64 and trained for up to 200 epochs with the Adam optimizer. To minimize random initialisation effects, each experimental condition is replicated more than 30 times. The experimental settings are summarized in Table 1.

Table 1. Computational and model configuration

Parameter	Configuration
Number of observations	10,000
System dimensions	5, 10, 20, 30, 50
Nonlinear coupling coefficient	0.05–0.40
Uncertainty levels	0%, 5%, 10%, 15%, 20%
Fuzzy states	Low, Medium, High
Pattern classes	Stable, Transitional, Complex/Unstable
Training/validation/testing	70% / 15% / 15%
Graph-learning layers	2
Optimizer	Adam
Learning rate	0.001
Batch size	64
Maximum epochs	200
Independent simulation runs	30

4.2 Comparative Methods

The proposed work is compared with the models MLP, GNN and Fuzzy GNN. The MLP gives a traditional non-linear learning baseline without explicit relational modeling, and the GNN is used to model the dependencies between different dimensions of the system. The Fuzzy GNN also includes uncertainty-aware fuzzy representations. The increasing effectiveness of these baselines allows for an assessment of the contribution of dimension-aware learning, pattern representation inspired by quantum computers, and minimax robustness to training and testing in the proposed framework.

4.3 Performance Metrics

Five metrics of performance are taken into account. The RMSE quantifies the nonlinear state-prediction error: the closer it is to zero, the better. MAE is the average absolute difference between the predicted and target states and a smaller value is better. The goodness-of-fit of the state prediction of the nonlinear model, measured by R^2, is higher for better explanatory performance. The accuracy assesses the overall percentage of patterns of nonlinear systems correctly identified, whereas the Macro F1-score offers a well-balanced classification assessment across the three classes (stable, transitional, complex/unstable). The metrics jointly validate prediction error, the quality of the nonlinear models and the capability of the pattern classification.

5. Results and Discussion

5.1 Overall Quantitative Performance

The overall quantitative comparison in Table 2 demonstrates a gradual improvement in performance from MLP to GNN, Fuzzy GNN and the proposed framework. MLP achieves an RMSE of 0.086, MAE of 0.067, R^2 of 0.884, Accuracy of 82.4%, and Macro F1-score of 0.811, whereas GNN improves these values to 0.071, 0.054, 0.913, 86.7%, and 0.859, respectively. When further incorporating fuzzy representation, the performance of the Fuzzy GNN is enhanced to RMSE=0.059, MAE=0.046, R^2=0.935, Accuracy=91.2%, and Macro F1-score is 0.904. The overall RMSE, MAE, R^2, Accuracy, and Macro F1-score values of the proposed framework (0.043, 0.034, 0.961, 94.6, 0.941) show that the proposed framework achieved improved nonlinear prediction and Balanced pattern classification with the help of the combination of fuzzy graph learning, dimension-aware learning, and quantum-inspired learning, and minimax learning.

Table 2. Overall performance comparison

Method	RMSE ↓	MAE ↓	R^2 ↑	Accuracy (%) ↑	Macro F1 ↑
MLP	0.086	0.067	0.884	82.4	0.811
GNN	0.071	0.054	0.913	86.7	0.859
Fuzzy GNN	0.059	0.046	0.935	91.2	0.904
Proposed Framework	0.043	0.034	0.961	94.6	0.941

The robustness analysis in Fig. 2 shows the effect of increase in uncertainty on the performance of the nonlinear state prediction for all comparative models. The MLP, GNN, Fuzzy GNN, and the proposed one achieve RMSE of 0.086, 0.071, 0.059 and 0.043, respectively, at 0% uncertainty, and the proposed method already shows the smallest prediction error. As uncertainty increases to 5%, the corresponding RMSE values rise to 0.094, 0.078, 0.064, and 0.046, while at 10% uncertainty they reach 0.106, 0.086, 0.070, and 0.050. Under stronger perturbations, the difference in the performance becomes greater. The RMSE of 0.119 for the MLP is 15% higher than that of the proposed framework, which is just 0.055, with GNN at 0.096 and Fuzzy GNN at 0.078.

Under the most severe 20% uncertainty, RMSE increases to 0.134, 0.108, 0.087, and 0.061, respectively. Hence, as uncertainty ranges from 0% to 20%, the RMSE values for MLP, GNN, Fuzzy GNN and Proposed framework are increased by around 55.8%, 52.1%, 47.5% and 41.9% respectively. The proposed method significantly outperforms MLP, GNN and Fuzzy GNN in all cases of high uncertainties with a gain of RMSE reduction of about 54.5%, 43.5% and 29.9% respectively. The bounds on point-set uncertainty and dependency modeling from the graph allows for better robustness against perturbations, and fuzzy dimension-aware learning brings a greater focus on informative dimensions, while the bounds on adverse conditions explicitly considers bounded adverse conditions in the learning process. Thus, the intent of the proposed framework to be robust to a growing level of uncertainty is confirmed with quantitative evidence as seen in Fig. 2, showing that nonlinear prediction performance does not degrade significantly as uncertainty grows.

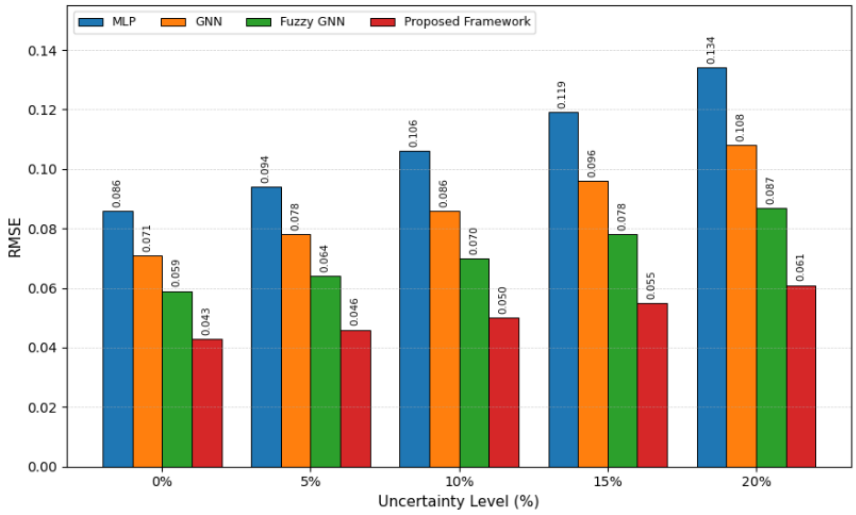


Fig. 2. RMSE performance under increasing uncertainty levels.

5.3 Effect of Increasing System Dimensionality

The dimensionality analysis shown in the figure 3 illustrates the performance of the classification based on the number of dimensions of the system. The MLP, GNN, Fuzzy GNN and proposed framework get an accuracy of 88.2%, 91.3%, 94.0% and 96.5% respectively at 5 dimensions. As the dimensionality grows to 10, the corresponding accuracies drop slightly: 86.4%, 89.8%, 92.8, and 95.8%. Given the proposed framework maintains an accuracy of 94.9%, MLP suffers from a drop to 83.9% accuracy at 20 dimensions and GNN and Fuzzy GNN show 87.5% and 91.4% accuracy respectively. For the proposed framework, the accuracies of MLP, GNN, Fuzzy GNN and proposed framework are 93.8%, 85.2%, 89.6% and 81.1% respectively for further 12 dimensions of increase to 30. The differences in performance increase at higher dimensionality (50) as MLP yields 77.6%, GNN 82.1%, Fuzzy GNN 86.8%, and the proposed framework 91.9%. Since the absolute accuracy drop is obtained across the whole dimensional range of 5 to 50, the absolute error reduction for the proposed framework is 4.6 points, as compared to 9.2 points for GNN, 7.2 points for Fuzzy GNN and 10.6 points for MLP. On the 50 dimensional data, the proposed approach shows the advantage of 14.3%, 9.8%, and 5.1% over MLP, GNN, and Fuzzy GNN, respectively. The smaller degradation suggests that fuzzy uncertainty representation, the use of graph-based dependency modeling, adaptive dimensional weighting, quantum-inspired pattern encoding, and minimax learning all help to preserve discriminative nonlinear information as the dimensionality increases. However, the opposite side of the scalability coin is that there are more graph nodes and dependencies, meaning that computational needs increase as well, and it would be worthwhile to consider the increase in these requirements in substantially higher-dimensional applications.

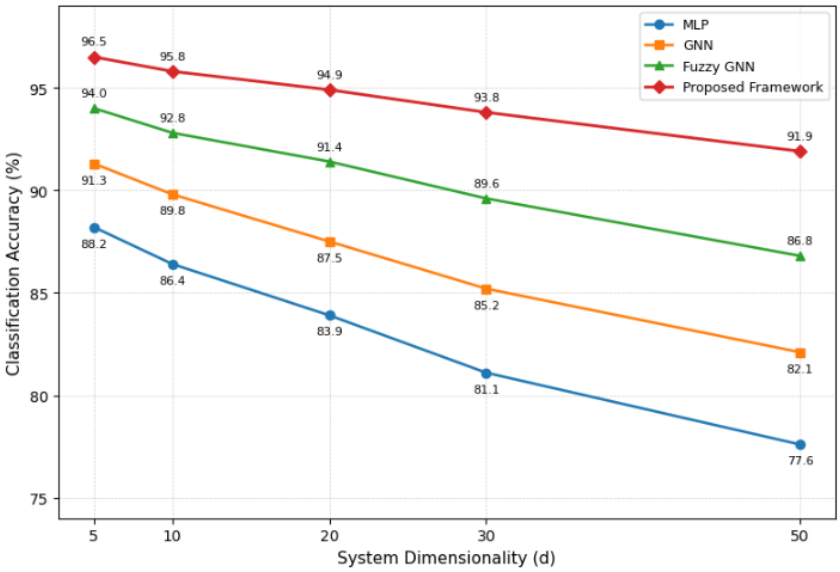


Fig. 3. Classification accuracy under increasing system dimensionality.

6. Conclusion

This study introduced a nonlinear dimensional analysis framework combining fuzzy graph theory, dimension-aware deep neural learning, quantum-inspired pattern representation and minimax optimization methodology for high-dimensional nonlinear systems with uncertainty. Fuzzy representation is used to represent uncertain variables by using gradual membership states and nonlinear graph construction techniques are adopted to capture dependencies between the interacting dimensions. The dimension-aware graph learning algorithm automatically highlights informative variables and creates a small nonlinear representation while the quantum-inspired encoding distinguishes the similarities and differences between stable, transitional, and complex/unstable patterns in the system. This robustness is further enhanced by the minimax optimization in the training of the models, where bounded adverse perturbations are also taken into consideration. The results show that the proposed framework outperforms the baselines MLP, GNN, and Fuzzy GNN in terms of the RMSE, MAE, R^2, and the classification Accuracy on the nonlinear prediction problem and the Macro F1-score on the pattern classification problem, giving a value of 0.043, 0.034, 0.961, 94.6%, and 0.941, respectively. The framework also demonstrates relatively low sensitivity to the increase of uncertainty and dimensionality of the system, suggesting strong robustness to perturbations and dimensionality. These results highlight the complementarities of fuzzy uncertainty modeling, nonlinear graph relationships, adaptive dimensional weighting, quantum inspired representation and worst-case minimax learning. However, the present investigation is restricted to nonlinear systems which are computed, with prescribed uncertainties, and higher dimensions come with extra costs for graph-processing and optimization. Expansion of the framework to bigger dynamic systems, real world data sets, adaptive uncertainty modelling, alternative minimax strategies and hybrid quantum/classical implementations will be studied in future to further evaluate the scalability and applicability of the proposed framework.

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