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Dimensionality-Aware Fuzzy Graph Neural Networks for Nonlinear Dynamical System Modeling and Quantum-Inspired Pattern Recognition

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Abstract

The problem of modeling nonlinear dynamical systems is still difficult due to the involvement of dynamic state evolution, transitions and nonlinear relations. Despite its strong performance in deep learning, the conventional neural network suffers from the inability to model relational structures, and the conventional graph neural network fails to explicitly consider fuzzy uncertainty and different relevance of latent features. In this work, a Dimensionality-Aware Fuzzy Graph Neural Network with Quantum-Inspired Pattern Recognition (DA-FGNN-QPR) is proposed for a 5D nonlinear dynamical system. Dynamic graphs are used to represent time-varying state interactions, and Low–Moderate–High fuzzy memberships are used to represent the uncertain operating regions. A mechanism based on the importance of the informative latent features is imposed to control the dimensionality, then quantum inspired amplitude-phase encoding is used to achieve complex pattern discrimination. The framework simultaneously functions as a means of predicting the next state and three-class recognition of Stable, Transitional, and Complex/Unstable regimes. The performance is compared with MLP, GNN and Fuzzy GNN using RMSE, MAE, R^2, Accuracy and Macro F1. The computational results show the value of RMSE is 0.043; MAE is 0.032; R^2, is 0.968; the accuracy is 94.6 % and the Macro F1 is 0.941, which represents better nonlinear modeling and pattern-recognition capability.

Keywords: Nonlinear dynamical systems, Fuzzy graph neural networks, Dimensionality-aware learning, Dynamic graph modeling, Quantum-inspired pattern recognition, State prediction.

1. Introduction

Nonlinear dynamical systems offer a mathematical and computational foundation for modelling complex processes in which variables are involved, their evolution over time, feedback and their mutual nonlinear relations. The more complex the dynamics, involving more than one state variable that are modified at the same time, and the more dynamic their interaction, the more challenging it is to model them correctly. Furthermore, it

is hard to predict states continuously and identify patterns due to ambiguous boundaries between different dynamical states. A potential means of overcoming this challenge is a representation of the system as a graph, where nodes represent the various system variables, and edges represent the various dependencies, these being adaptive in nature.A means of addressing this challenge is to make the system variables the nodes and the various relationships as adaptive edges, thus allowing the system to incorporate relational information as part of the learning process.

Most conventional neural models describe dynamics as feature vectors, which may not necessarily be sufficient to capture the dynamic relationships across the states. While graph neural networks (GNNs) have been found to perform well on relational modeling tasks, traditional architectures may assume a static or inadequate connectivity, impose a flat treatment on latent dimensions, and fail to represent various operating ranges. Dimensionality reduction, fuzzy uncertainty modeling and pattern recognition are also commonly dealt with separately. Therefore, the simultaneous representation of nonlinear interactions, fuzzy uncertainty, relevance of features according to dimensions, and complex transitional patterns is still a big challenge from computational point of view.

For this reason, the authors present DA-FGNN-QPR in this study. The main contributions are: (1) the five dimensional nonlinear system that models intrinsic evolution, saturation, coupling and perturbation; (2) construction of dynamic graphs with state dependent graph attributes; (3) feature-rich Stable, Transitional and Complex/Unstable pattern recognition; (4) dimensionality-aware weighting of informative graph features; (5) quantum-inspired amplitude-phase representation with no quantum hardware; (6) comparative, perturbation, dimensionality and ablation analyses. This paper is followed by related work in Section 2, proposed methodology in Section 3, computational evaluation in Section 4, results and discussion in Section 5 and conclusions and future directions in Section 6.

2. Related Work

Representing the temporal evolution, the equilibrium behavior, the stability and the nonlinear interactions of a nonlinear dynamical system has always been based on mathematical formulations and numerical integration techniques [5]. These methods have been extended by machine learning strategies that learn more complex mappings directly from multidimensional states [1] and deep neural networks that have the capacity to represent more complex temporal relationships [6]. But the traditional vector based learning may not be able to sufficiently capture explicit interactions between state variables when such interactions change over time, like for coupled variables [3].

A relational alternative is to use graph neural networks (GNNs), where the dynamical variables are represented as nodes of the graph, and the relationships between them are defined as the weights of the corresponding graph edges [12]. Graph convolution and message passing techniques allow information sharing between the connected states and learning of cross-variable dependencies [11]. Dynamic graph formulations also enable changing connectivity to change over time, related to temporal conditions [8]. However, classical GNNs can still be sensitive to the unknown graph relations and can poorly represent the dynamically different behaviors between regimes [15]. Recent dynamic graph representation approaches further emphasize learning continuously evolving relational structures [2].

Fuzzy learning offers a powerful tool for modeling uncertainty by modeling each state using a membership function that is not associated with a strict boundary and is somewhat fuzzy [13]. Gradual changes and indeterminate operating conditions can be described as Low, Moderate, and High memberships. Alongside, attention and dimensionality-aware models can emphasis more on informative latent dimensions while attenuating the importance of redundant ones [10]. Although these particular benefits, fuzzy representation and latent dimensionality selection have been implemented separately from dynamic graph learning.

These quantum-inspired pattern recognitions are computations that would be represented in a way inspired by quantum concepts, but without the need for a quantum processor [9]. Alternative learned feature-space representations of complex patterns are offered by Amplitude-phase encoding and relationships based on interference [7]. These are potentially applicable to the problem of distinguishing dynamical regimes with boundaries that show nonlinear and/or transitional behavior [4]. Hierarchical quantum-inspired feature representations have also demonstrated their potential for learning complex matching relationships [14].

Although these advancements have been achieved, it is still not possible to combine together dynamic graph learning, fuzzy reasoning, dimensionality-aware feature weighting and quantum-inspired pattern representation in a unified way. Besides, the continual state prediction and dynamical pattern classification problems are often

treated as two different problems. This encourages a common architecture that can learn the nonlinear state evolution dynamics as well as recognize the Stable, Transitional and Complex/Unstable dynamical patterns.

3. Proposed DA-FGNN-QPR Methodology

3.1 Nonlinear Dynamical System Modeling and Dynamic Graph Construction

The DA-FGNN-QPR approach starts by modelling the nonlinear dynamical process with five interactable state variables. At time t, the system state is expressed as

$$x(t) = [x_1(t), x_2(t), x_3(t), x_4(t), x_5(t)]^T, \quad (1)$$

Every state undergoes its own temporal dynamics, nonlinear saturation, interactions with the other states and an external perturbation term. The discrete-time evolution is given by the equation

$$x_i(t + \Delta t) = x_i(t) + \Delta t \left[a_i x_i - b_i x_i^2(t) + \sum_{\substack{j=1 \\ j \neq 1}}^{5} c_{ij} x_i(t) x_j(t) + u_i(t) \right], \quad (2)$$

where $\boldsymbol{a_i}$ denotes the intrinsic evolution coefficient, $\boldsymbol{b_i}$ controls nonlinear saturation, $\boldsymbol{c_{ij}}$represents the coupling strength between states $i$and j, and $\boldsymbol{u_i(t)}$ introduces time-dependent perturbation. The coefficients are varied within $\boldsymbol{a_i}$=0.20–0.80, $\boldsymbol{b_i}$=0.10–0.50, and $\boldsymbol{c_{ij}}$=0.05–0.40, while the state variables are maintained within the normalized range 0–1. A temporal step of $\Delta t = 0.01$ s is used, with perturbation levels ranging from 0% to 20%. To explicitly represent cross-state dependencies, the five-dimensional state vector is transformed at every time instant into a dynamic graph

$$G_t = (V, E_t, A_t), \quad |V| = 5, \quad (3)$$

where$V = \{x_1, x_2, x_3, x_4, x_5\}$represents the state nodes, E_t represents the time-dependent interactions, and At is the corresponding weighted adjacency matrix. Unlike a fixed graph, the interaction strengths are updated according to the current state configuration. The adaptive edge weight between nodes i and j is calculated as

$$A_{ij}(t) = c_{ij} exp\left[\frac{\left(x_i(t) - x_j(t)\right)^2}{2\sigma^2} \right], \quad i \neq j, \quad (4)$$

whereσ=0.25 controls the sensitivity of the similarity function. Connections with $A_{ij}(t) < 0.10$ are treated as negligible. As a result, highly similar and highly coupled states have larger values for their edge weight, while less coupled states have smaller weights.

The whole DA-FGNN-QPR architecture works on the nonlinear states using dynamic graph generation, fuzzy state representation, fuzzy graph neural learning, dimensionality aware feature selection, and quantum inspired pattern representation, to generate joint outputs, as shown in Fig 1. The first output is the next five-dimensional state vector and the second is classified as Stable, Transitional or Complex/Unstable for the current dynamical condition.

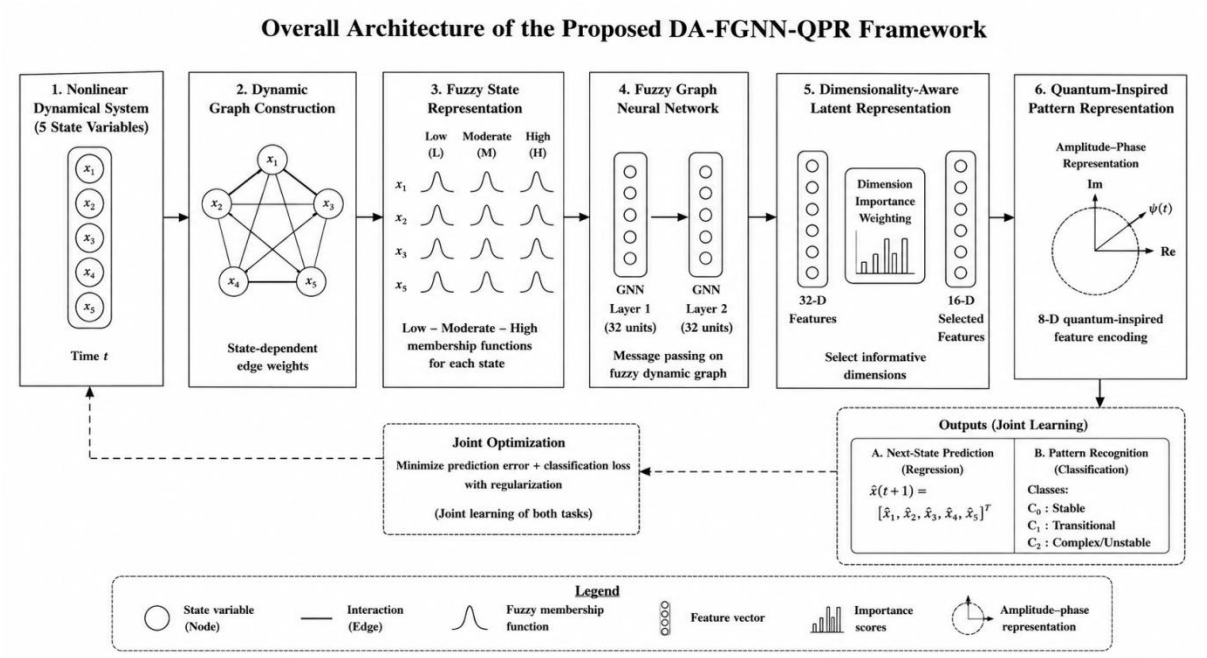


Fig. 1. Overall Architecture of the Proposed DA-FGNN-QPR Framework

The mechanism of dynamic interaction is further clarified in Fig. 2 where the nodes of the figure are the five state variables, while the lines are the time-varying magnitudes of the interactions. For the illustrated state configuration, stronger interactions such as$A_{45} = 0.90$, $A_{12} = 0.82$, and $A_{35} = 0.74$ indicate closely related dynamical states, whereas lower values such as $A_{14} = 0.37$, $A_{25} = 0.31$, $A_{13} = 0.28$, and $A_{24} = 0.23$represent comparatively weaker dependencies. These weights are not permanently assigned; they vary with the evolving values of x1–x5.This dynamic topology allows the following fuzzy graph neural network to learn state behavior as well as the state to state relationships that vary over time.

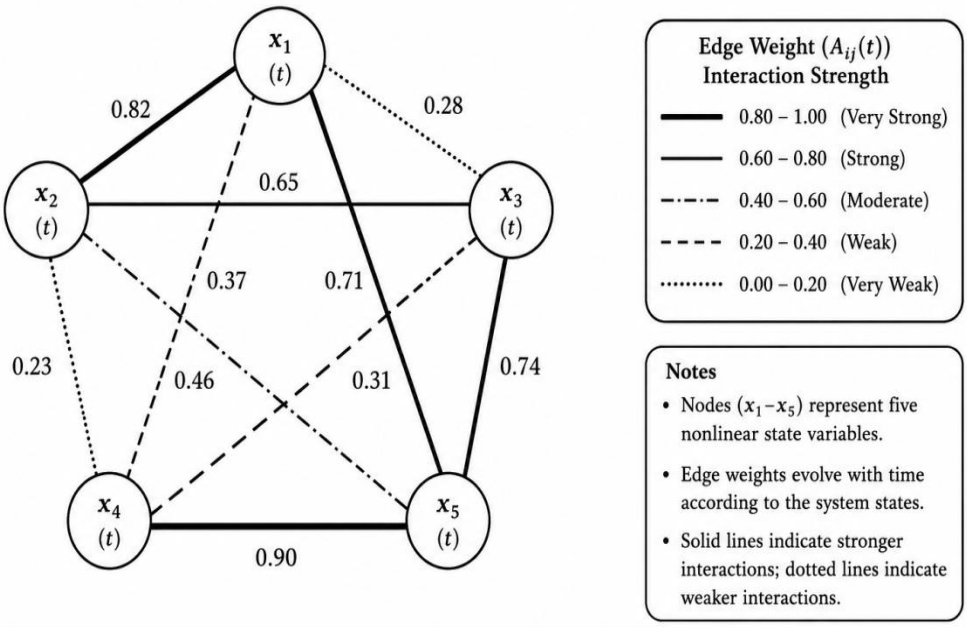


Fig. 2. Dynamic Five-Node Graph Representation of Nonlinear State Interactions

Table 1. Computational Configuration and Nonlinear Dynamical-System Parameters

Parameter	Symbol	Setting
Number of state variables	N	5
State range	x_i	0–1
Simulation duration	T	100 s
Time step	Δt	0.01 s
Samples per run	N_s	10,000
Computational runs	—	30
Evolution coefficient	a_i	0.20–0.80
Saturation coefficient	b_i	0.10–0.50
Coupling coefficient	c_{ij}	0.05–0.40
Graph similarity width	σ	0.25
Edge threshold	—	0.10
Perturbation level	ρ	0–20%

3.2 Fuzzy State Representation and Graph Feature Learning

The DA-FGNN-QPR framework proposed in the paper develops a fuzzy state representation to model uncertainty and gradual transitions of nonlinear state variables after the dynamic graph construction. Rather than assigning each state to a rigid interval, every normalized variable $x_i(t)$ is represented using three overlapping linguistic states**:** Low (L), Moderate (M), and High (H)**.**This representation is useful in regions near the dynamical transition boundaries, where the features of two neighbouring operating regions might be present in one state. The membership of the $i-$th state variable in fuzzy state r is determined using a Gaussian membership function:

$$\mu_{ir}(t) = exp\left[\frac{(x_i(t)-m_r)^2}{2s_r^2}\right], \quad r \in \{L, M, H\}, _____(5)$$

wherem_r and $s_r$denote the center and spread of fuzzy state r, respectively. The membership centers are set as m_L=0.20, m_M=0.50, and m_H=0.80, corresponding to Low, Moderate, and High operating regions. They are characterized by overlapping Gaussian profiles which prevent abrupt transitions between neighboring states, and help maintain uncertainty information during the nonlinear evolution. The membership values are normalized as to have a comparable representation for later graph learning as

$$\bar{\mu}_{ir}(t) = \frac{\mu_{ir}(t)}{\sum_{q\in\{L,M,H\}}\mu_{ir}(t)+\epsilon}, _____(6)$$

where$\boldsymbol{\epsilon}$ is a small positive constant introduced for numerical stability. Accordingly, each state variable contributes three normalized fuzzy memberships. Each state variable thus has three normalized fuzzy memberships. This generates 15 fuzzy features for the 5 dimensional dynamical system that together describe both the magnitude and uncertainty aspects of the current state of the system. The fuzzy representation thus obtained is coupled with the state dependent graph generated in Section 3.1. Graph message passing allows each node to adapt its representation based on available information from the dynamically connected neighbouring states. The fuzzy graph propagation at layer l is given by

$$H^{(l+1)} = \phi\left(\tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-1/2}H^{(l)}W^{(l)}\right), _____(7)$$

where$H^{(l)}$ denotes the node-feature matrix at layer l, $\tilde{A}$ represents the fuzzy-enhanced adjacency matrix, $\tilde{D}$ is its corresponding degree matrix, $W^{(l)}$contains the trainable graph transformation parameters, and $\phi(\cdot)$ denotes the nonlinear activation function. The framework is based on two GNN layers, both having 32 hidden dimensions. Thus, the fuzzy graph learning stage incorporates the uncertainty in the state information along with evolving inter-state relationships, resulting in a 32-dimensional latent representation for the dimensionality-aware processing stage as described in Section 3.3.

3.3 Dimensionality-Aware Latent Feature Representation

The fuzzy graph learning stage produces a latent representation of 32 dimensions, in which some of the dimensions could be more useful than others in the nonlinear state modeling and in pattern recognition. Failing to incorporate information about irrelevant dimensions could leave out potentially useful information and could make the learned representation less compact. Hence the proposed DA-FGNN-QPR includes a dimensionality

aware mechanism for estimating the significance of each latents feature extracted from the graphs prior to building the final compact representation. For each latent dimensionh_k, an importance score s_k is first obtained and converted into a normalized weight using

$$\alpha_k = \frac{exp(s_k)}{\sum_{r=1}^{d} exp(s_r)}, \quad (8)$$

where $d = 32$ denotes the original number of latent graph dimensions.This is achieved by using softmax normalization, such that dimensions with higher relevance scores get higher weights, dimensions with lower relevance scores get lower weights, etc. The feature representation is then created as

$$z_k = \alpha_k h_k, \quad Z = [z_1, z_2, \ldots\ldots, z_{d'}], \quad (9)$$

Here, z_k represents the weighted form of latent feature h_k, while d' denotes the number of retained dimensions. . The original 32 dimensional graph representation is compacted to 16 dimension-aware features in the main DA-FGNN-QPR configuration. Instead of direct truncation of the feature vector, the selection is done based on the learnt importance weights.

The dimensionality-aware process starts with the 2 layers of fuzzy GNN generated 32 features as seen in Fig. 3.An importance score is calculated for each feature dimension, followed by softmax-based conversion into the corresponding αk weights. Each latent feature is subsequently scaled using $z_k = \alpha_k h_k$, and the 16 dimensions with the highest importance are retained to form the compact representation. For instance weights of 0.082, 0.061 and 0.042 are assigned to comparatively informative dimensions, whereas 0.014 and 0.009 are assigned to lesser informative dimensions. This mechanism enables the framework to highlight informative nonlinear characteristics of graphs and to stop less informative components of the graph.

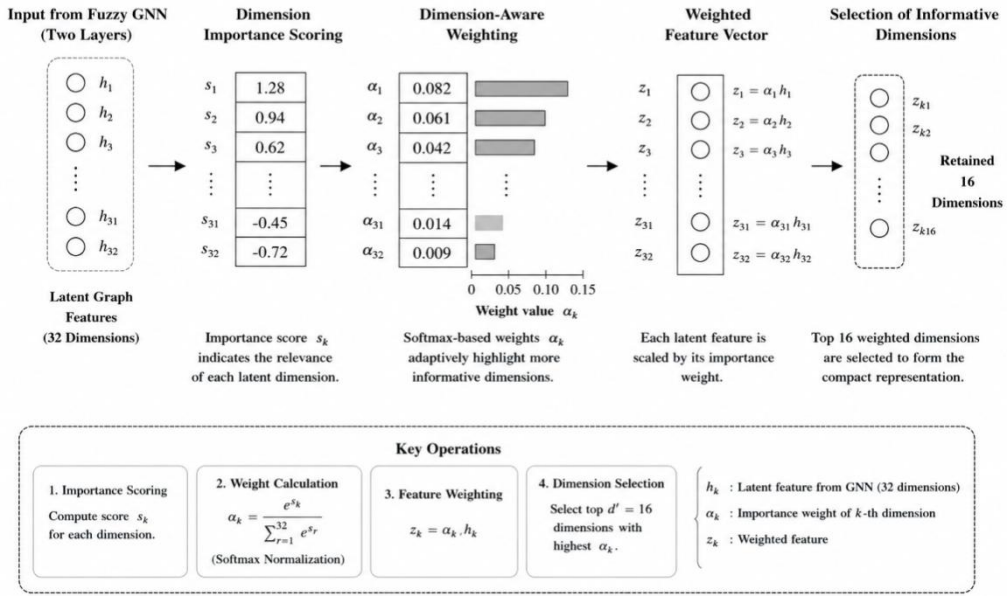


Fig. 3. Dimensionality-Aware Weighting and Selection of Latent Graph Features.

Dimensionality is also used to determine if the selected latent size is suitable by assessing the dimensionality using 4, 8, 16, 24 and 32 retained dimensions. This analysis can be used to decide whether adding too many features to a compressed representation introduces redundant information, or if compressing all of the features and discarding the linear details is detrimental to the preservation and discovery of the nonlinear. The chosen 16 dimensional representation is then passed on to quantum-inspired pattern representation stage (Section 3.4).

3.4 Quantum-Inspired Pattern Recognition and Output Prediction

Dimensionally aware feature selection is followed by projecting the selected representation into an eight-dimensional feature space designed based on quantum inspired features to enhance the discrimination between nonlinear dynamical patterns. The proposed approach does not involve quantum computation nor quantum hardware. Instead, it uses amplitude-phase encoding as a computational representation and the magnitude and

phase of the learned latent features complement each other to describe the complex and transitional behavior of the systems. The quantum-inspired state at time t is represented as

$$|\psi(t)\rangle = \sum_{k=1}^{8} a_k(t) e^{j\phi_k(t)} |k\rangle, \quad \sum_{k=1}^{8} |a_k(t)|^2 = 1, _____ (10)$$

where$a_k(t)$ denotes the normalized amplitude associated with the k-th quantum-inspired feature, $\phi_k(t)$ represents its phase component, $j = \sqrt{-1}$, and $| k\rangle$ denotes the corresponding basis state. The normalization condition is used to assure the sum of the squared amplitudes equals one. Differences in both feature magnitude and phase can be preserved during characterisation of nonlinear operating patterns through this representation. This representation is sent to the classification branch where three dynamical regimes are taken into account:

$$P(C_r|\psi) = \frac{exp(o_r)}{\sum_{q=0}^{2} \exp(O_q)}, \quad \boldsymbol{r} \in \{\mathbf{0}, \mathbf{1}, \mathbf{2}\}, _____ \mathbf{(11)}$$

whereo_r represents the output score associated with classC_r. The class having the highest probability is selected as the predicted dynamical pattern. It is important to note the distinction between the Transitional class and the other classes, because it is an intermediate behavior space between simple, stable operation and more complex, unstable system evolution. As a parallel process, a regression branch estimates the next state of the given nonlinear system as

$$\hat{x}(t+1) = [\hat{x}_1, \hat{x}_2, \hat{x}_3, \hat{x}_4, \hat{x}_5]^T$$

Therefore, DA-FGNN-QPR yields two complementary results of the common learned representation: a 5-dimensional prediction of the next state to model continuous dynamic systems and a 3-class probability distribution for pattern recognition. These outputs enable the framework to deduce on its own the evolution of the nonlinear system and the nature of the dynamic mode that is being exhibited, but keep the quantum-inspired part of the framework merely as a feature representation for the computation, without the need to imply that it is performed on a physical quantum processor.

3.5 Joint Optimization and Computational Procedure

Co-optimizing the two learning tasks: continuous next-state prediction and three-class dynamical-pattern recognition is the ultimate proposed DA-FGNN-QPR framework. Instead of training individual regression models and classification models, a shared representation is learned with the aim of optimizing the learned graph, fuzzy, dimensionality-aware and quantum-inspired features that will be utilized in both regression and classification. The overall objective is a combination of mean squared prediction error, categorical classification loss and an L2-regularization term as

$$\mathscr{L} = \lambda_1 \frac{1}{5N_s} \sum_{n=1}^{N_s} \|X_n(t+1)\|_2^2 - \lambda_2 \frac{1}{N_s} \sum_{n=1}^{N_s} \sum_{r=0}^{2} ynr \log P_{nr} + \lambda_3 \|\Theta\|_2^2, _____ (12)$$

The first term shows how close the 5-dimensional state vector is to the actual value; the second term shows how close the classification of the 3 classes is to the actual value; the third term is for preventing the parameters from becoming too large. The weighting coefficients are fixed at $\lambda_1 = 0.55, \lambda_2 = 0.40$and $\lambda_2 = 0.05$, giving slightly greater emphasis to nonlinear state prediction while maintaining a substantial contribution from pattern classification.

The entire computational sequence is 5 states, 15 fuzzy features, GNN-32, GNN-32, DA-16, QPR-8, and then a regression and three-class classification. A set of five normalized non-linear state variables are first converted to 15 fuzzy memberships, followed by two graph neural layers that consist of 32 hidden features. The 16 informative dimensions are kept in the dimensionality-aware module and then projected to an eight-dimensional quantum-inspired representation before the two output branches are evaluated.

Table 2 shows a summary of the architectural and training situations. The optimization algorithm used is Adam optimization and the learning rate is 0.001, batch size is 64 and 150 epochs of training. To prevent overfitting, a 0.20 dropout rate is used. The generated temporal samples are partitioned into a training set (70%), validation set (15%), and testing set (15%) and the entire procedure is repeated 30 times with different computational run conditions, to determine consistency when the model is initialized and is trained in different ways.

Table 2. DA-FGNN-QPR Architecture, Training, and Evaluation Configuration

Parameter	Setting

Primary state variables	5
Fuzzy memberships per state	3
Fuzzy input features	15
GNN layers	2
Hidden dimension per GNN layer	32
DA retained dimensions	16
QPR dimensions	8
Pattern classes	3
Optimizer	Adam
Learning rate	0.001
Batch size	64
Training epochs	150
Dropout rate	0.20
Train/validation/test split	70/15/15%
Repeated computational runs	30

The architecture gradually shrinks the learned representation from 32 graph features to 16 dimension-aware features and then to 8 quantum-inspired elements prior to joint output prediction, as can be seen in Table 2. This staged design employs a hierarchy of designs designed to retain informative nonlinear dependencies without redundant latent information and will enable simultaneous regression and classification to be done within one unified framework.

4. Computational Evaluation Setup

The computational testing aims to evaluate the nonlinear state-prediction and dynamical-pattern recognition ability of the proposed DA-FGNN-QPR framework in a consistent training and testing setup. Four methods are taken into consideration: MLP, Standard GNN, Fuzzy GNN and DA-FGNN-QPR. The MLP is a baseline with a traditional vector representation, while the Standard GNN investigates the advantages of relational graph learning and the Fuzzy GNN explores the impact of uncertainty-aware graph representation. The same data partition, optimizer settings, learning rate, batch size and number of epochs are used where applicable, to provide a fair comparison.

There are, in fact, precisely five key metrics that are used to measure model performance. RMSE gives the overall size of the error in the prediction of the next-state, while its MAE gives the average of the absolute difference between the predicted and the reference value for the states. The coefficient of determination, R^2, assesses the goodness of fit of each one to the evolution of the nonlinear state. In the three-class pattern-recognition problem, the Accuracy (%) is defined as the percentage of correctly classified Stable, Transitional, and Complex/Unstable states and the Macro F1-score evaluates the performance of three classes equally.

Three Evaluation Scenarios are taken into account apart from the main method comparison: Apart from the main method comparison there are three focused Evaluation Scenarios taken into account: Robustness is evaluated for the perturbation levels of 0%, 5%, 10%, 15% and 20% To study if excessive compression or unnecessary feature retention has detrimental effects on performance, the dimensionality analysis is looking at the retained latent representations of 4, 8, 16, 24, and 32 dimensions. Lastly, the full variant of the DA-FGNN-QPR is compared with variants that remove fuzzy representation, remove the dimensionality-aware mechanism, and remove the quantum-inspired pattern-recognition component. These assessments work together to provide an integrated measure of the effectiveness of the framework as well as separate measures of each of the key elements.

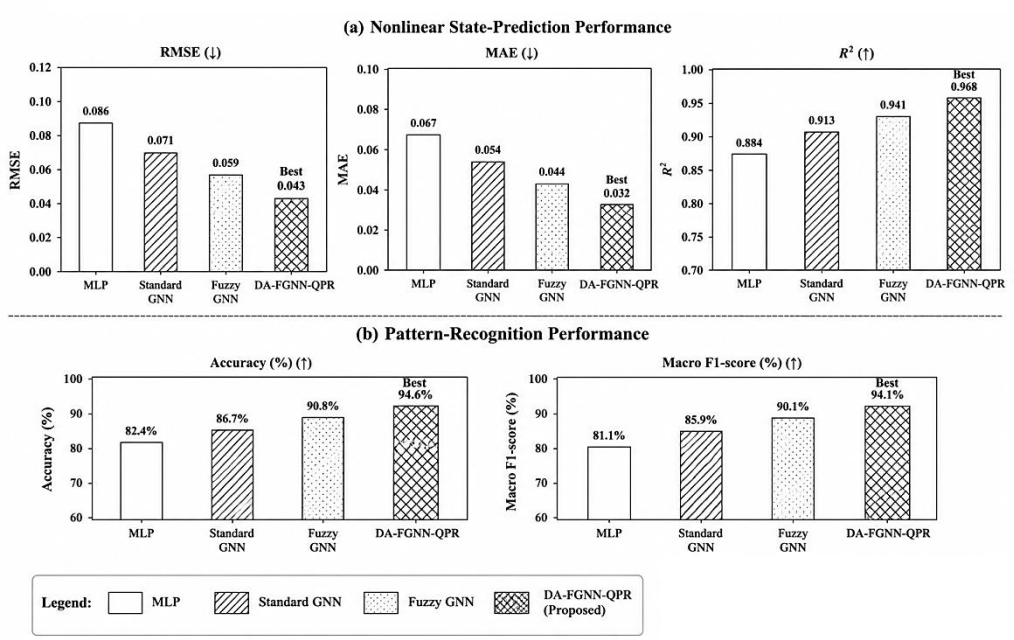


Fig. 4. Comparative performance of the evaluated methods: (a) state prediction and (b) pattern recognition.

5. Results and Discussion

5.1 Overall Nonlinear State Prediction and Pattern Recognition

The overall performance of the four methods assessed are summarized in Table 3, and shown graphically compared in Fig. 4. As reported in Table 3, the MLP obtains 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. These values are enhanced with relational learning with the Standard GNN at 0.071, 0.054, 0.913, 86.7%, and 0.859 respectively. To further minimize the prediction errors, the Fuzzy GNN reduced the RMSE and MAE to 0.059 and 0.044, respectively, and the R^2, accuracy, and Macro F1-score to 0.941, 90.8%, and 0.901, respectively.

The proposed DA-FGNN-QPR shows the best overall performance with an RMSE of 0.043, MAE of 0.032, R^2 of 0.968, accuracy of 94.6% and Macro F1-score of 0.941. The proposed framework can achieve about 39.4% and 40.7% reduction in the RMSE and MAE compared to the Standard GNN, respectively, and a 7.9 percentage point increase in the classification accuracy. The improvements show the collective effect of fuzzy uncertainty representation, dimensionality-aware feature weighting and quantum inspired pattern encoding.

As shown in Figure 1, the RMSE and MAE are lowest for DA-FGNN-QPR and the R^2 is the highest, which indicates that DA-FGNN-QPR has better nonlinear next-state prediction. The same can be observed in Fig. 4(b) in case of three-class pattern recognition, where the proposed method gives the best Accuracy and Macro F1-Score. The stable development of MLP to Standard GNN, Fuzzy GNN, and DA-FGNN-QPR demonstrates feature learning contribution of relational, uncertainty-aware and dimension-sensitive elements.

Table 3. Comparative Nonlinear State Modeling and Pattern-Recognition Performance

Method	RMSE ↓	MAE ↓	R^2↑	Accuracy (%) ↑	Macro F1 ↑
MLP	0.086	0.067	0.884	82.4	0.811
Standard GNN	0.071	0.054	0.913	86.7	0.859
Fuzzy GNN	0.059	0.044	0.941	90.8	0.901
DA-FGNN-QPR	0.043	0.032	0.968	94.6	0.941

Fig. 4. Comparative performance of the evaluated methods: (a) state prediction and (b) pattern recognition.

5.2 Perturbation Robustness Analysis

An evaluation of the perturbation robustness of the methods is carried out by raising the level of perturbation from 0% to 20%. For the case of 0% perturbation, DA-FGNN-QPR is the most accurate method with accuracy of 96.1%, followed by the Fuzzy GNN with accuracy 93.4%, the Standard GNN with accuracy 90.2%, and

finally, the MLP with accuracy 87.6%. The proposed framework can preserve the accuracy of 95.5% and 94.6% for the perturbation of 5% and 10% respectively, while MLP can only preserve the accuracy of 84.9% and 81.8% for the same perturbation of 5% and 10% respectively. Under higher perturbation levels of 15% and 20%, DA-FGNN-QPR retains 92.3% and 89.6% accuracy, compared with 88.1% and 84.7% for Fuzzy GNN, 82.8% and 78.5% for Standard GNN, and 77.2% and 71.9% for MLP.

The accuracy drop of DA-FGNN-QPR is just 6.5 percentage points worse than Fuzzy GNN's 8.7 points drop and 11.7 points drop for Standard GNN and 15.7 points drop for MLP, respectively, across the full perturbation range. The relatively slow degradation suggests more robust representation of uncertainty and overlap in state space with the fuzzy representation, and maintenance of cross-state relationships that change with time using dynamic graph learning. The dimensionality-aware mechanism also enables less informative features to be suppressed under disturbed conditions, which helps to keep the pattern-recognition performance high with the growth of disturbance severity, and thus allows the DA-FGNN-QPR to maintain high performance.

5.3 Dimensionality Sensitivity Analysis

The effect of latent dimensionality is tested by using 4, 8, 16, 24 and 32 dimensions in the dimensionality-aware representation. The 4 retained dimensions provide 89.7% accuracy, showing that too much compression is not capturing useful information to differentiate the nonlinear dynamical patterns. A greater number of dimensions (8) leads to a higher accuracy (93.1%), and the highest is with 16 dimensions (94.6%). Additional dimensions (1024 and 16384) only improve accuracy slightly to 94.2% and 93.8%, respectively.

The results show that it is not always beneficial to increase latent dimensionality in order to achieve higher recognition accuracy. A highly compressed representation can lose out on valuable cross-state relationships while a large number of dimensions can capture where there are redundancies in the graph or weak relationships. This results in the best information-preservation feature-compactness of the 16-dimensional configuration. This behavior is beneficial for the dimensionality-aware component of DA-FGNN-QPR, which utilizes informative latent features instead of the whole 32-dimensional GNN representation.

5.4 Component Ablation Analysis

The individual removal of the fuzzy representation, dimensionality-aware mechanism and quantum-inspired pattern representation is investigated to examine the contribution of each of the principal components of DA-FGNN-QPR. The best performance is obtained when all those elements are combined together, with an RMSE of 0.043, the accuracy of 94.6% and a Macro F1 score of 0.941. The elimination of the fuzzy representation makes the RMSE value more 0.052 and reduces the accuracy and Macro F1 values to 91.7% and 0.910 respectively. This is the greatest reduction in accuracy of 2.9 percentage points, which shows that fuzzy memberships are important to represent dynamical states with uncertainty and overlap. In absence of the dimensionality-aware weighting, RMSE value is 0.050, accuracy is 92.3%, and Macro F1 is 0.917, which results in a 2.3-point drop in accuracy. This justifies the focus on informative graph dimensions, while damping redundant latent features. Removing the quantum-inspired pattern representation brings the model to an RMSE of 0.047 and an accuracy of 93.0% and an Macro F1 of 0.925. As mentioned, this is set to be a smaller but significant decrease in accuracy from the model.

These components are shown together in the behavior of Fig. 5. Although the accuracy drops at 20% perturbation (Fig. 5(a) between 96.1% and 89.6%), it shows an accuracy degradation of just 6.5 percentage points, making DA-FGNN-QPR the accuracy benchmark for perturbation level 20% and below. The framework is also dimensionally sensitive as shown in Fig. 5(b) where accuracy improves from 89.7% for 4 dimensions to 94.6% for 16 dimensions, and then slightly decreases to 94.2% and 93.8% for 24 and 32 dimensions, respectively. Lastly, the ablation of the fuzzy representation, dimensionality awareness, and QPR shows that the accuracy of 94.6% is the highest with all three components, compared to that of 91.7%, 92.3%, and 93.0% for removing one of the three at a time, as seen in Fig. 5(c). Together, these results suggest that all three elements are important for ultimate performance; and that their combination is most effective for non-linear modeling and pattern recognition.

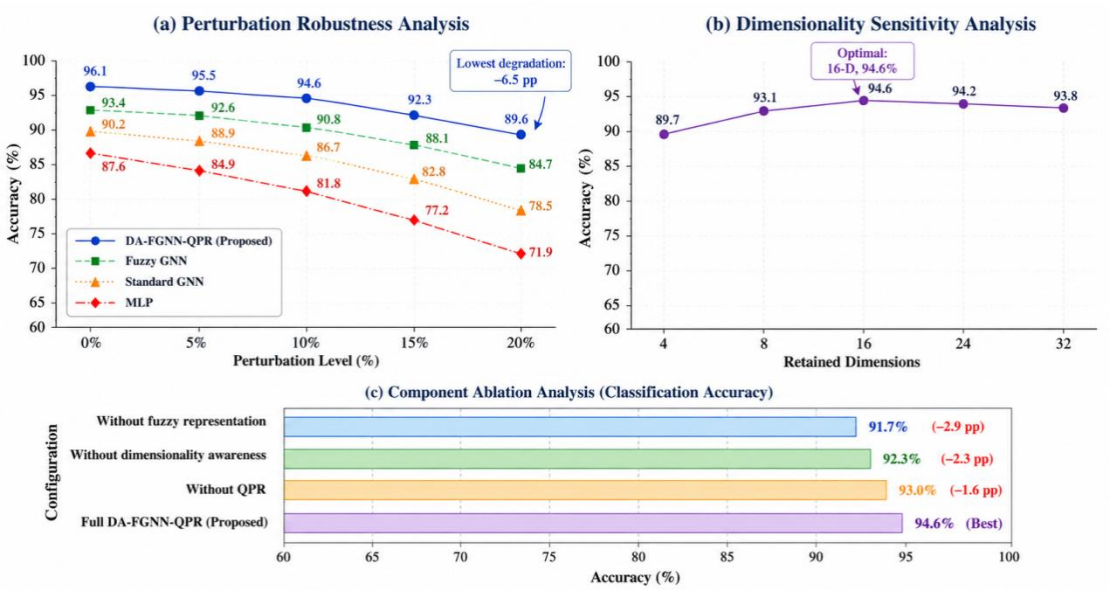


Fig. 5. DA-FGNN-QPR analysis: (a) perturbation robustness, (b) dimensionality sensitivity, and (c) component ablation.

6. Conclusion and Future Work

This study proposed to combine the advantages of adaptive graph construction, fuzzy state representation, dimensionality-aware learning, and quantum-inspired feature processing to provide a unified computational framework for modeling and pattern recognition of nonlinear dynamical systems: DA-FGNN-QPR. The dynamic graph formulation allows evolving dependencies between the five interacting state variables to be modeled as state-dependent edge weights, instead of fixed relationships. Operating conditions are further captured and transitions are also uncertain by the addition of the Low, Moderate and High fuzzy memberships. The dimensionality-aware mechanism extracts informative latent graph features whose dimensionality is reduced from 32 to 16 so as to not convey redundant information. An amplitude-phase encoding inspired by quantum computing is then used for a further representation that can be used to distinguish complex dynamical patterns without the need of quantum hardware. The framework simultaneously estimates and classifies to Stable, Transitional and Complex/Unstable regimes. Computational evaluation yielded an RMSE of 0.043, MAE of 0.032, $R^2$of 0.968, accuracy of 94.6%, and Macro F1-score of 0.941. Robustness analysis also demonstrated that the accuracy was not significantly affected when the individual components of the model were removed, and when the model was perturbed by 20% the accuracy was found to be 89.6%. This study shows the complementary value of fuzzy reasoning, dimensionality-aware learning and quantum inspired representation. Higher dimensional and bigger state spaces will be explored in future work, as will automatically learnt graph topologies, adaptive fuzzy membership functions and temporal graph architectures. More research will be undertaken on domain specific applications, real measurement based validation, hardware acceleration, hybrid quantum/classical systems, and running on actual quantum computing hardware.

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