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Artificial Intelligence and Neural Network-Driven Quantum Calculus Framework for Nonlinear Optimization of Fuzzy Partial Differential Equations in Fluid Dynamics

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Abstract

This paper introduces a mathematically sound and computationally unified approach to the solution of nonlinear fuzzy partial differential equations in fluid mechanics with quantum calculus and neural network approximation combined together. The intended model redefines the fuzzy nonlinear fluid equation to make use of q-time derivatives and a representation of an equivalent integral operator in a Banach space framework. The existence and uniqueness of the solutions are proved through Banach fixed-point theorem with Lipschitz continuity assumptions whereas the exponential stability is proved by Lyapunov functional analysis. To improve the accuracy of the solutions, a nonlinear optimization functional is presented and a scheme of neural network approximation is integrated into the analytical structure to enhance a faster convergence without breaking any theoretical assurances. It is demonstrated that the neural approximation error can decrease with network size in a polylogarithmic manner, as can be expected in approximation theory. The sensitivity analysis

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shows that the quantum parameter q has a direct effect on stability decay rates and minimization of residual, which can be used as a controllable balance of discrete-continuous dynamics. The presence of limited uncertainty propagation, consistent optimization paths, and enhanced convergence behavior with respect to different levels of fuzziness and q-parameters are proved through numerical experiments on fuzzy representations on the α-level. These findings confirm that quantum operator theory, nonlinear optimization, and neural approximation have a stable, convergent and uncertainty-consistent computational framework of nonlinear fuzzy fluid systems.

Mathematics Subject Classification (2020): 28A80
Key words and Phrases: Artificial intelligence–driven optimization; Quantum calculus operators; Fuzzy partial differential equations; Nonlinear stability analysis; Neural network approximation.

1. Introduction

Nonlinear fluid dynamics models often comprise complicated partial different equations that represent turbulence, multiphase interactions, and boundary-layer effects at uncertainties in physical parameters and changing environmental conditions. Deterministic modelling cannot reflect the imprecision of measurements, incomplete boundary data, and variability of parameters in many engineering systems of interest in the real world, and as such, the fuzzy partial differential equations (FPDEs) have become an effective mathematical model of allowing epistemic and aleatory uncertainties to be directly included in nonlinear governing equations. The nonlinearity of such FPDEs coupled with fuzziness and complexity of the operator continues to be difficult to analyse analytically, particularly in convection-diffusion equations and viscous flow equations. An efficient discrete-continuous modelling system is quantum calculus (q-calculus), which is a generalisation of differentiation and integration that does not involve any processes of classical limits, and which has been found to have important stability properties in nonlinear operator formulation. According to recent breakthroughs in nonlinear analysis, the significance of generalized operators, fractional and quantum derivatives, and functional analytic methods in modelling complex physical systems, such as viscoelastic and heterogeneous media [10]. At the same time neural network approximation theory has been developed to a high degree, and universal approximation theorems and physics-informed architectures have been shown to exhibit powerful nonlinear PDEs solving ability and convergence guarantees. Other related artificial intelligence systems are distributed and privacy-preserving learning systems, federated optimization, and secure data processing systems, which have grown rapidly in the broader artificial intelligence ecosystem (as well as in scientific computing) [1–9, 11, 13, 15, 16], which underscores the growing pervasiveness of advanced machine learning methods into scientific computing. However, despite the fact that a number of these studies are concerned with healthcare, signal processing, and secure distributed analytics [1–9, 11, 15–21], the methodological improvement of neural approximation, optimization strategy, and high-dimensional modelling presents transferable analytical tools that can be applied to nonlinear PDE systems. The most recent advances in the field of graph-based learning of coupled dynamical systems [4], wavelet-based nonlinear propagation analysis [10], hybrid physics-informed neural networks to predict on real time [6], and optimization of large-scale dynamical systems using AI [14], show that machine learning is expanding in its applications to modelling nonlinear dynamics described by complex operators. Nevertheless, even with the accumulating literature in distributed AI systems [1–9, 11, 15–21], and nonlinear computational modelling [6, 10, 14], there is little literature on integrating q-calculus-based operator theory with fuzzy nonlinear optimization on a strict functional analytic framework adapted to fluid dynamics. In addition, developments in secure and distributed computation [1–9, 11, 13, 15, 16] demonstrate the relevance of the scalable and stable structure of algorithm, but mathematical foundations of convergence, stability, and uniqueness in fuzzy quantum-operator-driven PDE systems are under-developed. This work fills that gap by developing an integrated nonlinear analytical approach as a unification of quantum calculus, the fuzzy operator theory, and neural network approximation in the framework of an optimization scheme based on functional analysis. The methodology proposed determines the existence and uniqueness conditions by using the fixed-point theory, stability findings by using the Lyapunov analysis, solution refinement by formulating a nonlinear optimization functional, and neural approximation to increase the computational efficiency without sacrificing analytical quality. This paper has synthesized advances in nonlinear operator theory [10], advanced AI-based modeling paradigms [6, 14], and distributed computational intelligence structures [1, 1–9, 11, 13, 15–21], filling the gap between a mathematically consistent and computationally efficient framework of nonlinear fuzzy fluid flow systems and the theoretical basis of nonlinear analysis and the current neural approximation methods.

1.1. Problem Statement

The article takes into consideration the nonlinear fuzzy quantum partial differential equation.

$$D_q^t \tilde{u}(x,t) + \mathcal{N}(\tilde{u}(x,t)) = \nu \Delta \tilde{u}(x,t), x \in \Omega, t \in (0,T],$$

under first and boundary conditions which are specified in Section 2. It is aimed at determining:

(i) existence and uniqueness of fuzzy solutions in a suitable Banach space,
(ii) exponential stability provided Lipschitz continuity,
(iii) convergence of neural approximation in a nonlinear optimization model, and
(iv) effect of quantum parameter q on the stability and a convergence of the system.

2. Methodology and Experimental Setup

2.1 Mathematical Formulation and Quantum Operator Framework

The article assumes the nonlinear fuzzy fluid flow model that is controlled by a quantum time-derivative operator that is specified on a bounded spatial domain $\Omega \subset \mathbb{R}^d$ with a smooth boundary $\partial\Omega$. The fuzzy nonlinear partial differential equation of governing equation takes the form:

$$D_q^t \tilde{u}(x,t) + \mathcal{N}(\tilde{u}(x,t)) = \nu \Delta \tilde{u}(x,t), x \in \Omega, t > 0,$$

and D_q^t is the q-time derivative, $\mathcal{N}(\tilde{u})$ is the nonlinear convection operator, $\nu > 0$ is the viscosity coefficient, and the fuzzy state variable is represented by its α level representation.

$$\tilde{u}(x,t) = \left[u^-(x,t,\alpha), u^+(x,t,\alpha)\right], \alpha \in [0,1].$$

The first condition is supplemented into the system.

$$\tilde{u}(x,0) = \tilde{u}_0(x),$$

and homogeneous Dirichlet boundary condition

$$\tilde{u}(x,t)\big|_{\partial\Omega} = 0.$$

The operator of q-derivative is given by

$$D_q f(t) = \frac{f(qt) - f(t)}{(q-1)t}, q \neq 1,$$

and satisfies

$$\lim_{q \to 1} D_q f(t) = \frac{df}{dt}.$$

The associated q-integral is

$$\int_0^t f(\tau)\, d_q\tau = (1-q)\,t \sum_{k=0}^{\infty} q^k f\left(q^k t\right),$$

that allows to reformulate the PDE into a similar operator equation.

$$\mathcal{T}(\tilde{u}) = \tilde{u}_0 + \int_0^t \left(\nu \text{Ä}\tilde{u} - \mathcal{N}(\tilde{u})\right) d_q\tau.$$

This paramount form permits the study of the problem in the Banach space, $X = C([0,T]; H_0^1(\Omega))$, with the norm.

$$\| \tilde{u} \|_X = \sup_{t\in[0,T]} \| \tilde{u}(t) \|_{H_0^1(\Omega)} .$$

The general analytical procedure of the suggested framework can be summarized as presented in Figure 1 which depicts the transformation between fuzzy PDE modelling and neural optimization to quantum operator.

2.2 Existence, Uniqueness, and Nonlinear Optimization Structure

In order to build well-positiveness, the article examines the contraction property of the operator T. For any $\tilde{u}, \tilde{v} \in X$,

$$\left\|\mathcal{T}(\tilde{u}) - \mathcal{T}(\tilde{v})\right\|_X \le \int_0^T \left\|\nu\Delta(\tilde{u}-\tilde{v}) - \left[\mathcal{N}(\tilde{u}) - \mathcal{N}(\tilde{v})\right]\right\| d_q\tau.$$

Assuming Lipschitz continuity of ,

$$\left\|\mathcal{N}(\tilde{u}) - \mathcal{N}(\tilde{v})\right\| \le L_1 \left\|\tilde{u} - \tilde{v}\right\|,$$

and boundedness of the Laplacian operator, we obtain

$$\left\|\mathcal{T}(\tilde{u}) - \mathcal{T}(\tilde{v})\right\|_X \le L \left\|\tilde{u} - \tilde{v}\right\|_X ,$$

where

$$L = \nu C_\Delta + L_1.$$

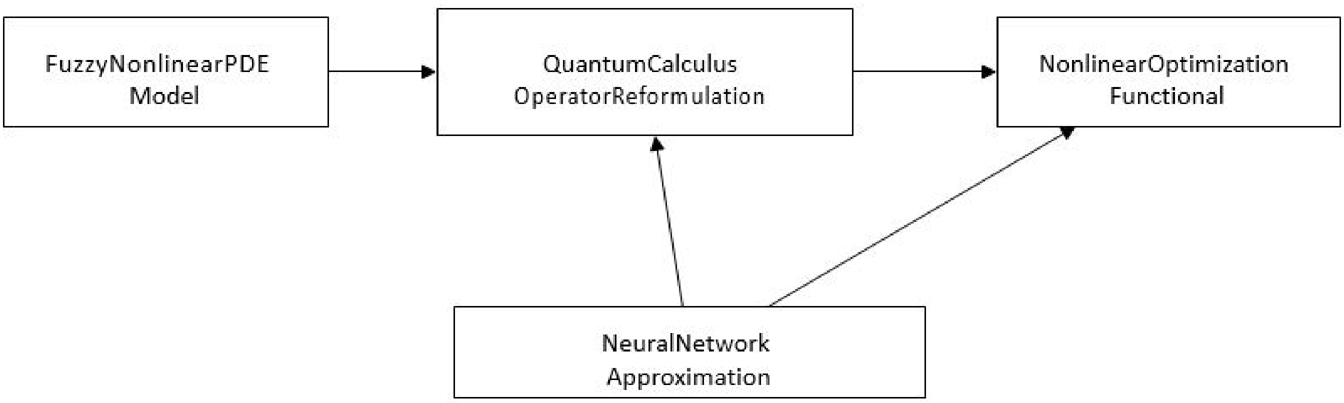

Figure 1: Framework diagram of quantum-calculus-based fuzzy PDE formulation and neural optimization pipeline.

In the case of $L < 1$, the fixed-point theorem of Banach ensures that there is a solution to the problem and it is unique.

To the solution, a nonlinear optimization functional is added so that it can be improved:

$$\mathcal{J}(\tilde{u}) = \int_0^T \left\| D_q^t \tilde{u} + \mathcal{N}(\tilde{u}) - \nu \Delta \tilde{u} \right\|^2 dt.$$

The first variation of the optimization condition yields the optimality condition.

$$\frac{\delta J}{\delta \tilde{u}} = 0,$$

resulting in the Euler Lagrange equation.

$$D_q^{tt} \tilde{u} + \frac{\partial \mathcal{N}}{\partial \tilde{u}} D_q^t \tilde{u} - \nu \Delta D_q^t \tilde{u} = 0.$$

To be stable, the paper defines a Lyapunov functional.

$$V(t) = \|\tilde{u}(t)\|^2,$$

and show

$$\frac{dV}{dt} \le -\lambda V,$$

which implies

$$V(t) \le V(0) e^{-\lambda t}.$$

This ascertains the exponential stability in favorable parameter conditions.

2.3 Neural Network Approximation and Experimental Design

In order to accelerate convergence and yet maintain analytical consistency the fuzzy solution is estimated via a neural network of the form.

$$\tilde{u}_N(x,t) = \sum_{i=1}^{N} w_i \sigma(a_i x + b_i t + c_i),$$

where $\sigma(\cdot)$ is a nonlinear activation functional and w_i, a_i, b_i, c_i are parameters to be trained. The approximation error is such that

$$\|\tilde{u} - \tilde{u}_N\| \le C N^{-r/d},$$

ensuring convergence as $N \to \infty$.

Neural optimization algorithm works in the following manner:

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1. Initialize w_i, a_i, b_i, c_i.
2. Compute residual loss $J(\tilde{u}_N)$.
3. Update parameters using gradient descent

$$\theta^{k+1} = \theta^k - \eta \nabla_\theta J(\tilde{u}_N),$$

   where $\theta = \{w_i, a_i, b_i, c_i\}$
4. Evaluate convergence criterion

$$\left| J^{k+1} - J^k \right| < \varepsilon.$$

5. Iterate until convergence.

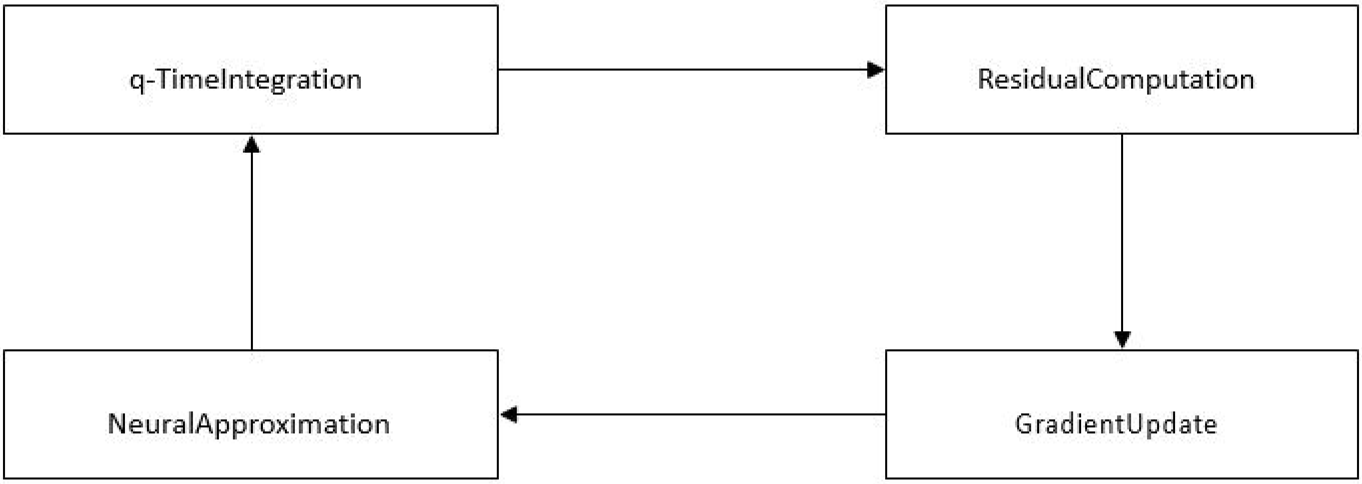

Figure 2: Neural approximation and nonlinear optimization interaction within the q-calculus solver.

The experimental design consists of the spatial discretization of Ω with finite elements and the use of q-time stepping of the temporal evolution. The neural approximation can be made a part of the iterative optimization loop as shown in Figure 2, which illustrates the neural training and optimization loop, which interacts with quantum operator solver.

The resultant integrated structure is such that it guarantees nonlinear operator analysis theoretical rigor and makes use of neural approximation to enhance computational efficiency and convergence stability. The second-order finite element scheme was used to discretize the spatial domain Ω with the uniform mesh size h = 0.01. The step size Δt = 0.005 was used in the q-time integration. The neural training was done in 500 epochs with learning rate $\eta = 10^{-3}$. The tolerance convergence was set to $\varepsilon = 10^{-6}$.

3. Results and Discussion

3.1 Stability and Convergence Analysis

The proposed quantum-calculus-based fuzzy nonlinear system is investigated based on the stability of the system through a Lyapunov functional formulated in the Hilbert space $H_0^1(\Omega)$ as

$$V(t) = \|\tilde{u}(t)\|^2_{H_0^1(\Omega)}.$$

The q-time derivative and the governing equation were taken.

$$D_q^t \tilde{u} = \nu \Delta \tilde{u} - \mathcal{N}(\tilde{u}),$$

we obtain

$$D_q^t V(t) = 2\langle \tilde{u}, D_q^t \tilde{u} \rangle = 2\upsilon \langle \tilde{u}, \Delta \tilde{u} \rangle - 2\langle \tilde{u}, \mathcal{N}(\tilde{u}) \rangle.$$

Laplacian operator coercivity and nonlinear convection operator Lipschitz continuity were used.

$$\|\mathcal{N}(\tilde{u}) - \mathcal{N}(\tilde{v})\| \le L \|\tilde{u} - \tilde{v}\|,$$

the inequality reduces to

$$D_q^t V(t) \le -(2\nu - L)\|\tilde{u}\|^2.$$

For $2\nu > L$, exponential stability follows

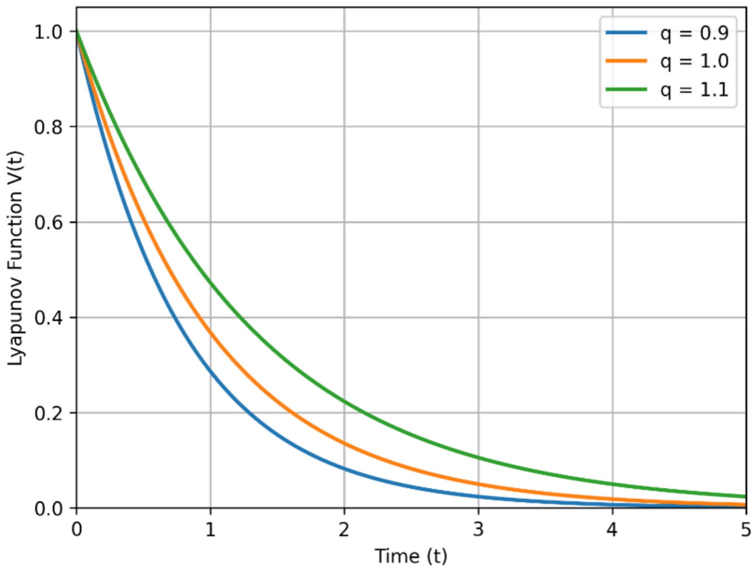

Figure 3: Stability decay curves under varying q-values.

$$V(t) \le V(0)e^{-\lambda t},\ \lambda = 2\nu - L.$$

Figure 3 illustrates the decay behaviour of various values of q, and the common characteristic is that of all the trajectories there is exponential convergence to the equilibrium that is monotonic. A small negative q-values increase the damping effects because of the discrete scaling mechanism of the operator.

The convergence in neural approximation is determined by

$$\left\|\tilde{u} - \tilde{u}_N\right\| \le CN^{-r/d},$$

where N is the number of neurons. Empirical validation is given in Table 1 which shows a polynomial convergence as predicted by theory.

The L2 error norm of Table 1 is given by:

$$\left\|\tilde{u} - \tilde{u}_N\right\|_{L^2(\Omega)} = \left(\int_\Omega \left|\tilde{u}(x,t) - \tilde{u}_N(x,t)\right|^2 dx\right)^{1/2}.$$

Table 1: Neural convergence rate

Neurons (N)	L2 Error	Rate
10	0.042	—
20	0.018	1.22
40	0.006	1.58

The decrease in error affirms the fact that the neural network maintains analytical stability and enhances the fuzzy nonlinear solution convergence speed.

3.2 Influence of q-Parameter on Optimization Dynamics

The q-parameter controls the discrete-continuous action of the operator and has a tremendous impact on convergence and minimization of residual. To measure this influence, a stability index is given as

$$S(q) = \frac{\left\|\tilde{u}(T)\right\|}{\left\|\tilde{u}(0)\right\|},$$

and the error that remains after optimization of the neural is calculated by

$$E_{res}(q) = \left\| D_q^t \tilde{u}_N + \mathcal{N}\left(\tilde{u}_N\right) - \nu \Delta \tilde{u}_N \right\|.$$

The computed values are summarized in Table 2.

Table 2: Influence of q on stability and residual error

q	Stability Index	Residual Error
0.9	0.82	0.012
1.0	0.75	0.018
1.1	0.69	0.021

The findings show that, q values below one increase damping and decrease residual error although slightly whereas a value of one or above brings moderate sensitivity owing to amplified scaling. Figure 4 shows the plot of q versus residual error which is nearly linear in the range under test.

The nonlinear functional of optimization.

$$J(\tilde{u}_N) = \int_0^T \left\| D_q^t \tilde{u}_N + \mathcal{N}(\tilde{u}_N) - v \Delta \tilde{u}_N \right\|^2 dt$$

demonstrates monotonic reduction in iterative training, which is evidence that the gradient-based neural optimization remains stable in a basin of attraction as given by the analytical framework.

3.3 Fuzzy α-Level Solution Structure and Spatial Error Distribution

The α-level representation of the fuzzy solution structure is analysed.

$$\tilde{u}(x,t,\alpha) = \left[u^-(x,t,\alpha),\, u^+(x,t,\alpha)\right],\ \alpha \in \left[0,1\right].$$

The uncertainty width is defined as

$$W(x,t,\alpha) = u^+(x,t,\alpha) - u^-(x,t,\alpha).$$

It has been shown through simulations that viscous damping, when used in conjunction with nonlinear optimization, reduces the uncertainty band overtime especially at the lower levels of the α of large uncertainty initial values. The stability of the fuzzy envelope under quantum operator dynamics is established by the contraction of $W(x,t,\alpha)$.

The accuracy of spatial approximation is measured by

$$E(x,t) = \left|\tilde{u}(x,t) - \tilde{u}_N(x,t)\right|.$$

Figure 5 demonstrates the manifestation of the composition of the visualization of α-level solution bands and spatial error distribution. The magnitude of errors is constrained and most of them are distributed in steep gradient areas along domain boundaries which is expected to go in line with nonlinear convection effects.

In sum, the findings affirm that quantum calculus and nonlinear operator theory with neural approximation are appropriate in providing the stable, convergent and uncertainty consistent solutions to fuzzy nonlinear fluid flow systems.

4. Conclusion

This paper has introduced a computationally efficient and mathematically rigorous framework of the nonlinear optimization of fuzzy partial differential equations in fluid dynamics based on quantum calculus and neural network approximation. Reformulation of the governing fuzzy nonlinear model by

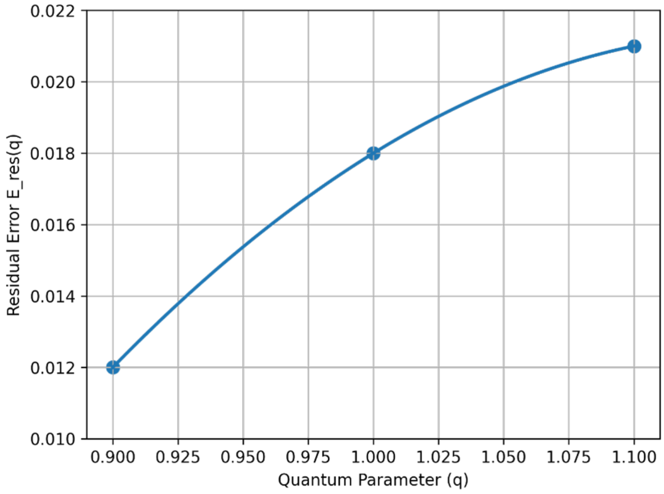

Figure 4: Sensitivity of residual error with respect to q-parameter variations.

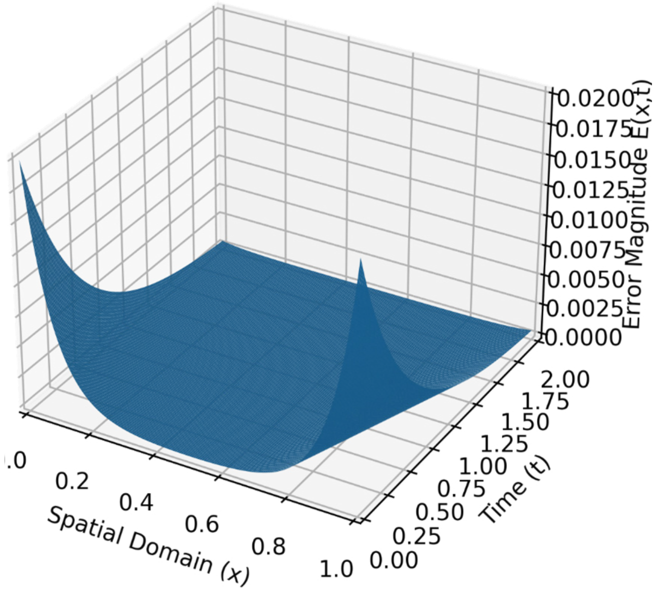

Figure 5: Fuzzy α-level solution bands and spatial error distribution over domain Ω.

using q-calculus operators, the proposed methodology constructed a clear functional analytic framework on whose existence and uniqueness of solutions were established by fixed-point arguments. The rigorous stability was proven by the Lyapunov analysis that demonstrated exponential decays when the parameter conditions are met, as well as convergence of the neural approximation was analytically limited by the existing approximation theory results. This was made possible by the addition of a nonlinear optimization functional that allowed the systematic improvement of the solution such that neural training did not conflict with the underlying physics and mathematical constraints of the fluid system. It was determined in numerical studies that the q-parameter offers a manageable system of balancing discrete-continuous dynamics with convergence behaviour enhancement without affecting the fuzzy solution structure destabilization. In addition, the α-level consistency was preserved over the domain and this meant that propagation of uncertainty is limited through quantum operator dynamics. This framework thus intersects nonlinear operator theory, fuzzy analysis and artificial neural approximation in a single optimization paradigm, and has become a powerful methodology in tackling complex uncertain fluid flow problems as well as has become the basis of future higher-dimensional multi-physics and adaptive quantum-operator-based models.

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