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Neural Operator-Based Surrogate Modeling for Real-Time Multiphysics Simulation and Control

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ABSTRACT

Multiphysics simulations are widely used in the modelling of engineering and scientific systems with complex geometries; where traditional numerical methods like finite element and finite difference methods have a high computational cost, their application in real-time is very limited. In this paper a neural operator-based surrogate modeling framework will be introduced that allows to perform efficient and accurate real-time multiphysics simulation and control. The proposed method takes advantage of state-of-the-art operator learning methods, such as the Fourier Neural Operator (FNO), Deep Operator Network (DeepONet), and Physics-Informed Neural Operator (PINO) to train the maps between input parameter spaces and the solution fields of governing partial differential equations. The framework combines both a high predictive accuracy and high physical consistency by incorporating the use of data-driven learning and physical constraints. Massive testing of the models has shown that the models are able to attain very high levels of computational latency reduction, with high fidelity, measured by indices like Relative L2 Error, Root Mean Squared Error (RMSE). Moreover, the surrogate model is smoothly combined with a control module, which allows making decisions in real time and optimising the system. The findings demonstrate that neural operator-based surrogates can be an effective solution to close the computational efficiency to physical accuracy gap, making them a potential solution to the next-generation real-time Multiphysics simulator and control system.

1. INTRODUCTION

The basis of modeling of complex systems where many physical phenomena interact, including fluidstructure interaction, thermal transport and electromagnetic processes, is based on multiphysics simulations. Applications of these simulations in aerospace design, energy systems, biomedical engineering and optimization of industrial processes are widespread. The correct numerical solution of the governing partial differential equations (PDEs) is however usually based on the classical methods like the finite element method (FEM) and the finite difference method (FDM) which are computationally intensive and in most cases do not allow real-time implementation in dynamic and control-driven systems [1], [2]. The growing need to have high-resolution simulations only adds to the burden on computational costs, and the traditional techniques are no longer suitable in time-sensitive applications. Recent developments in scientific machine learning have provided data-driven methods of learning solution operators of PDEs, to overcome these limitations. Specifically, neural operator architectures, including the Fourier Neural Operator (FNO) and Deep Operator Network (DeepONet), have shown the ability to learn operations between infinite-dimensional spaces of functions, to afford rapidly approximate complex physical systems [3]–[5]. These methods offer a paradigm shift between pointwise solution learning to operator learning, wherein generalisation over some different initial and boundary conditions is possible. Moreover, physics-informed learning methods, such as physics-informed neural networks (PINN) and Physics-Informed Neural Operator (PINO) directly introduce governing equations into the training, enhancing physical consistency and predictive robustness [6], [7].

Irrespective of these developments, there are a number of issues which have not been addressed. The current neural operator-based approaches are mainly concerned with the accuracy of offline predictions and are typically not combined with real-time-controlling systems. Also, the potential of

surrogate modeling to closed-loop control systems, which have rapid inference and stability as important criteria, is not fully exploited by most existing methods. Also, the trade-off between computational efficiency and physical fidelity in multiphysics systems has not been fully tackled especially in the real-time context. We suggest a neural operator-based surrogate modeling framework of multiphysics simulation and control in real-time in this work. The suggested scheme also takes advantage of powerful operator learning models, such as FNO, DeepONet, and PINO, to build the effective surrogate models that could be used to approximate high-dimensional solutions of PDEs with a lower computational cost. The framework is also combined with a control module, providing the real-time decision and optimisation of the system. The maximum assessment is carried out in the basis of well-known accuracy measures like Relative L2 Error and Root Mean Squared Error (RMSE) as well as performance measures based on the latency of calculations and control.

In this work, a single neural operator-based surrogate modeling framework is presented, which considerably decreases the calculation cost and still has a high predictive accuracy Multiphysics simulations. It can make inference in real-time by exploiting effective operator learning architectures, and quickly approximate PDE solutions in different conditions. Moreover, the framework suggested combines surrogate modeling and control strategies which allow optimizing a closed-loop system in real-time conditions. Lastly, an overall assessment is conducted based on accuracy and performance that illustrates effectiveness of the approach to close the divide between computational efficiency, physical consistency and real-time applicability.

2. RELATED WORK

The Multiphysics simulation has traditionally relied on classical numerical tools, including finite element method (FEM), finite difference method (FDM) and computational fluid dynamics (CFD) solvers. These techniques have become popular in computing complex partial differential equations (PDEs) of fluid flow, heat transfer, and structural interactions because they have a solid mathematical basis and are highly accurate. They are however more expensive in terms of computational costs and memory requirements, particularly in high-dimensional and nonlinear systems [1], [2]. Consequently, their real-world applicability, especially in control systems and digital twins, is drastically impaired.

To address these shortcomings, recent developments in the field of scientific machine learning have coined neural operator-based methods on learning mappings between function spaces. The Fourier Neural Operator (FNO) is an operator that makes use of spectral convolution in the Fourier domain effectively capturing globally dependent features in PDE solutions, which makes it possible to infer quickly and scale-involved [3], [4]. Deep Operator Networks (DeepONet) can be seen as an extension of this idea by a branch-trunk structure where it is possible to learn nonlinear operators with strong theoretical guarantees [5], [6]. Also graph-based operator learning techniques, including Graph Neural Operators and message-passing neural PDE solvers, have been suggested that can manage irregular geometries and mesh-based representations to be more flexible to real-life Multiphysics problems [7]. The methods are highly competitive in accuracy and also their computational complexity is much lower, increasing their potential as surrogate models.

Simultaneously, the concept of physics-informed learning has become one of the potent paradigms in the field of data-driven modeling that incorporates the domain knowledge. Physics-Informed neural networks Physics-Informed neural networks (PINNs) use governing equations, initial conditions, and boundary constraints directly as part of the loss function, allowing the exploration of limited amounts of data while maintaining physical consistency [8]. Nonetheless, PINNs are prone to inefficiencies in training and scalability in intricate Multiphysics. To solve these problems, Physics-Informed Neural Operators (PINO) are based on operator learning with physics-based constraints, which enhance both accuracy and convergence of high-dimensional PDEs [9], [10]. These mixed methods can be shown to be more generalizable and resilient than pure data-driven models.

Although these innovations have been made, the current approaches mainly consider ways of enhancing the accuracy of the prediction and generalization, and little concern has been shown on real-time deployment and integration of control. Majority of neural operator based systems are developed to perform offline simulation and are not coupled with control strategies needed to optimize a dynamic system. Moreover, the joint problems of the high computational efficiency, physical fidelity, and the possibility of the stable closed-loop control have not been investigated seriously. This gap is also emphasized by the fact that Multiphysics environments lack a comprehensive real time validation. This, hence, poses a definite necessity of an integrated framework that incorporates neural operator-based surrogate modeling with real-time simulation and control, as well as making sure that accuracy and computational efficiency is achieved.

3. METHODOLOGY

The objective of the proposed methodology is to come up with a neural operator-based surrogate modeling scheme to have an efficient and real-time system of multiphysics simulation and control. Coupled partial differential equations (PDEs) of fluid flow, heat transfer, and structural dynamics are typical governing equations of multiphysics systems. These systems can be generally expressed as nonlinear PDEs of the form:

$$\mathcal{F}(u, \nabla u, \nabla^2 u, x, t; \lambda) = 0 \quad (1)$$

Where u(x,t) represents the state variables, x and t denote spatial and temporal domains, and λ corresponds to system parameters. Rather than solving these equations directly through computationally intensive numeric, the task of this work is to be able to learn a mapping of input functions (e.g., initial conditions, boundary conditions, and system parameters) to output solution fields. This operator learning problem can be set as:

$$\mathcal{G}: a(x) \longrightarrow u(x) \quad (2)$$

Where G represents the operator of solutions which finds solutions to the PDE given an input functions a(x). The suggested framework estimates this operator with neural networks to allow the quick and scalable inference.

Fig 1 shows the end-to-end data generation to real-time control integration architecture of the proposed framework. The first step involves creating high-fidelity simulation data with standard numerical solvers, e.g., FEM or CFD, in order to build training datasets. These datasets can be used to capture a variety of system configurations, boundary conditions and changes in parameters. The training pipeline consists of training the operator mapping based on neural operator models, where the network parameters are trained to minimize prediction error and, in some cases, physics-based constraints. At inference, this trained model is implemented as a surrogate, which allows real-time prediction of system states at a much lower computational cost than the costs of the traditional solver.

In order to learn the underlying operator effectively, this work uses three fundamental neural operator models. The Fourier Neural Operator (FNO) is spectral convolution using the Fourier domain to learn global variation in spatial domains. FNO is a high-computational-efficiency long-range interaction model that converts input features to the frequency domain, applies learnable filters, and converts back to the spatial domain. Deep Operator Networks (DeepONet) are based on a branch-trunk architecture, in which the branch network learns functions by encoding input functions, and the trunk network learns spatial coordinates, allowing operator learning to be flexible across function spaces. This architecture has high generalization with different input conditions. Besides this, the Physics-Informed Neural Operator (PINO) uses physical constraints as part of the learning process by including PDE residuals in the loss. This guarantees that the learned operator fits data in addition to obeying physical laws governing it hence enhancing robustness and physical consistency.

In an effort to boost the computational efficiency, a surrogate modeling approach is included with the aid of dimensionality reduction methods. Techniques like Proper Orthogonal Decomposition (POD) or autoencoder based latent space learning are used to down-sample high-resolution simulation data. Training of the neural operator models in this reduced latent space is then done resulting in a much lower computational complexity but still capturing key system dynamics. In inference, the latent representations estimated are recreated as complete-field solutions and hence can quickly and precisely approximate multiphysics behavior.

Lastly, the proposed framework has an inbuilt control module to allow the optimization of the system in real time. A Model Predictive Control (MPC) controller is used, and the neural operator-based surrogate makes fast predictions of the future states of the system. The predictions are fed back to calculate optimal control actions within system constraints. The combination of surrogate modeling and control facilitates closed-loop decision-making with the lowest latency, which is why the framework can be used in time-sensitive scenarios, like smart grids and autonomous systems development as well as in controlling industrial processes.

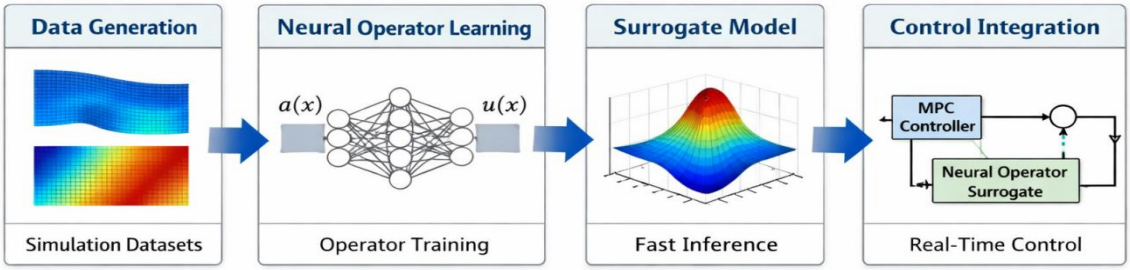


Fig 1. Neural Operator-Based Framework for Real-Time Multiphysics Simulation and Control.

4. Experimental Setup

The experimental system will help to test the efficiency of the developed neural operator-based surrogate modeling framework to simulate and control real-time Multiphysics. The analysis is done under representative Multiphysics problems, such as fluid dynamics, thermal diffusion, and structural deformation, which are all coupled partial differential equations (PDEs). Conventional numerical solvers are used to produce high-fidelity datasets so as to have the correct ground truth solutions. The simulations conducted on structural spatial grids with different resolutions are used to measure the scalability and generalization of the models. Boundary and initial conditions are systematically perturbed to probe a variety of physical situations, with Dirichlet and Neumann boundary conditions, and with the goal of being robust to a variety of operator configurations.

Fig 2 gives an idea of the overall experimental process, showing how data was generated, and models trained, validated, and then inferred in real-time along with the control loop. The derived datasets are separated into training, validation and test sets to have an unbiased testing. The training step involves acquisition of the operator map between input conditions and solution fields whereas the test step assesses the capability of the model to extrapolate to unobserved conditions. This pipeline allows the overall evaluation of the predictive accuracy and real-time performance.

Benchmarking of the proposed method is done by comparing it to classical numerical solvers, such as finite element method (FEM) and finite difference method (FDM), which is used as the ground truth in assessing accuracy. Moreover, physics-informed neural networks (PINNs) also represent deep learning-based baseline to test improvements in computational efficiency and physical consistency. These base techniques can give a good comparative benchmark of the benefits of neural operator-based surrogate models in both speed and accuracy.

The modern deep learning libraries are utilized in the implementation of the proposed framework, as well as implemented with the use of a modern deep learning library, which includes the acceleration on a computer (Gpu). Essential training parameters are number of epochs, batch size, and learning rate that have been hydrated to generate stable convergence and high predictive performance. The stochastic gradient-based optimization is used to train the models, and its loss functions integrate data-driven metrics of error and (where applicable) physics-based constraints. Training Hardware configurations consist of high-performance GPUs, evaluation Hardware configurations consist of standard CPUs, making sure that it is practically applicable in resource-constrained systems. This configuration will enable an equitable and holistic assessment of the efficiency of the computation, scalability, and applicability to real-time Multiphysics simulation and control.

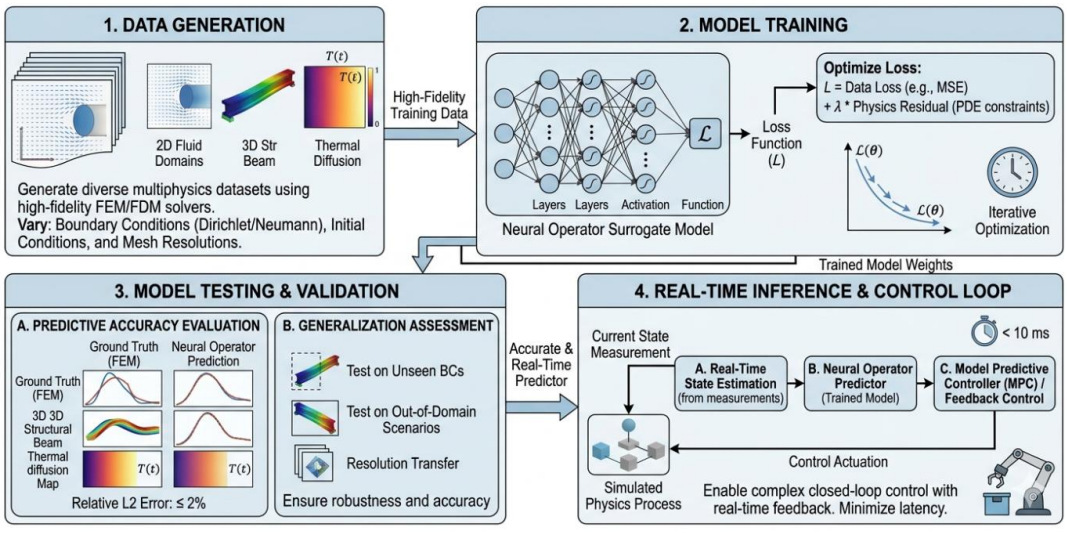


Fig 2. Experimental Workflow for Real-Time Simulation and Control.

5. Evaluation Metrics

The effectiveness of the suggested neural operator-based surrogate modeling platform is assessed by a broad array of measures that are reflective of the predictive performance, physical consistency, computation cost, and control performance. These measures are carefully chosen in order to illustrate the numerical accuracy of Multiphysics simulations as well as the applicability of the proposed approach in real-time. To determine the predictive accuracy, conventional error-based measures are used. The average squared error (MSE) is the

measure of the performance of a model by a general measure of average squared error between predicted and ground truth solution fields. Root Mean Squared Error (RMSE) is an additional interpretation of this deviation in the original scale of the data, and is more intuitive to assess physical quantities. Besides, the Relative L2 Error is used as the main measure because it is successful in identifying normalized differences in the spatial domains, especially when dealing with PDE based systems in which the magnitudes of solutions can be very different. These accuracy measures provide a stringent test of the capability of the surrogate model to give accurate numerical approximations of high-fidelity solutions.

In addition to a numerical accuracy, physical consistency is considered to make sure that the learned models obey the governing equations and the boundary conditions. PDE residual error is derived by substituting prediction with the actual equation of state of the original equations and it quantifies the degree to which laws of physics are upheld. Also, boundary condition violations are measures of how well the model adheres to the desired constraints at the boundaries of the domain. These measures are important towards justifying the soundness of neural operator-based models in science and engineering. Computational efficiency is taken into account to assess the real-time performance. The inference time indicates the time it takes to make predictions with the trained surrogate model, indicating its applicability in time-intensive situations. In addition, the computation time is compared to the conventional numerical solvers like FEM, which proves the computational superiority of the method proposed. These are direct measures of the ability of the framework to facilitate real-time Multiphysics simulation. Last but not least, the control-oriented metrics are used to evaluate the effectiveness of the integrated control module. The difference between the desired and actual system states during a closed-loop system operation is measured using tracking error. Moreover, the stability features, such as overshoot, settling time, are studied to assess the dynamic performance of the system under controller operation by the surrogate model. These measures combined will guarantee the proposed framework with high accuracy in simulation, as well as stability and performance in real-time control settings.

6. RESULTS AND DISCUSSION

The functionality of the suggested neural operator-based surrogate model was measured in predictive accuracy, computational efficiency, physical consistency, and effectiveness in control. The results obtained demonstrate that the framework can achieve high-fidelity Multiphysics predictions and that the computational cost is significantly decreased, which is crucial in real-time simulation and control cases.

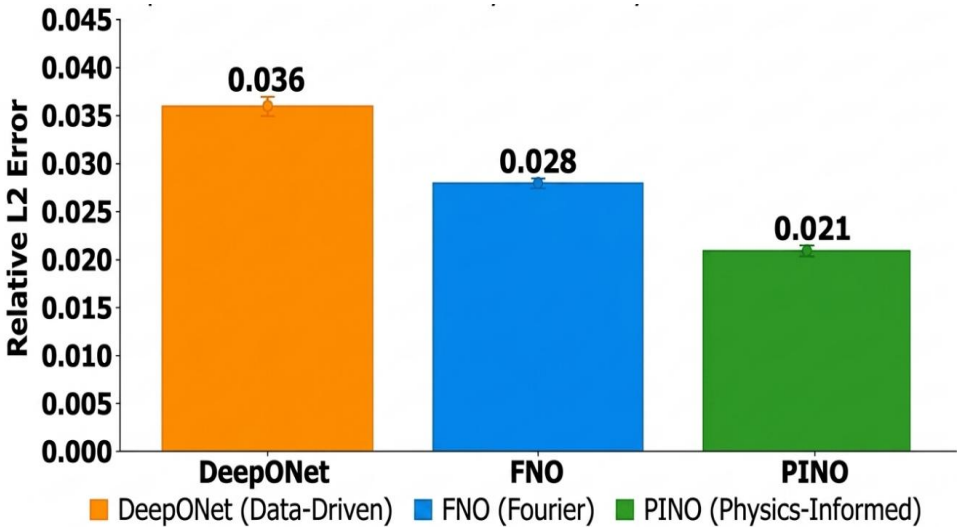


Fig 3. L2 Error Comparison across Neural Operator Models.

Fig 3 shows the Relative L2 error comparison among the three neural operator models, i.e., DeepONet, FNO and PINO, in the fluid dynamics case. Based on the results, it is evident that PINO has the least Relative L2 Error at 0.021, then FNO with 0.028, and DeepONet with the highest error of 0.036. This pattern suggests that inclusion of physics-based constraints of PINO enhances the capacity of the model to retain the underlying physics of the PDE system. Conversely, DeepONet, which relies more on data, has a relatively larger error since it relies more on the distribution of the training data, and does not explicitly require the physical consistency. FNO out is superior to DeepONet since its spectral convolution process can better capture global solution behavior, in

particular, in structured spatial spaces. On the whole, Fig 3 proves that PINO is represented as the best surrogate model among the tested models and it is important to integrate operator learning and physics-constrained models.

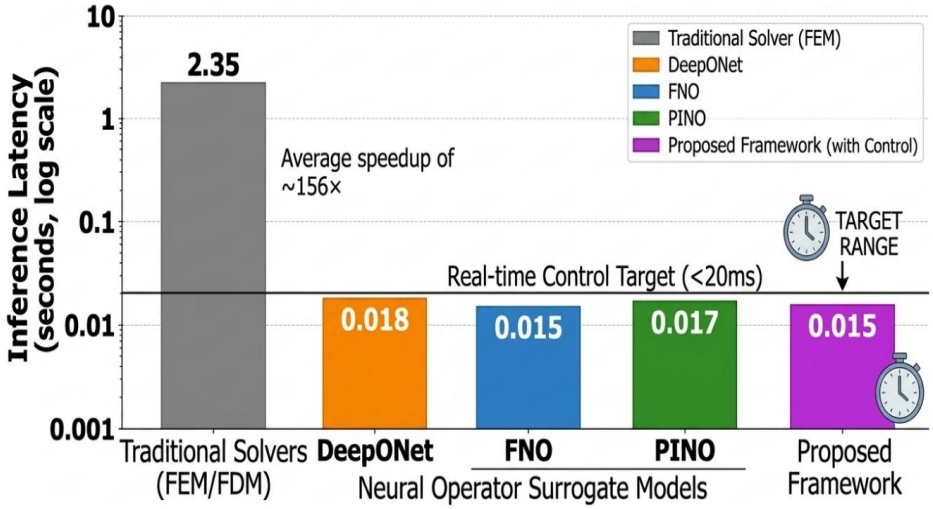


Fig 4. Inference Time Comparison across Methods.

Fig 4 shows the comparison of inference time between conventional numerical solvers, and neural operator-based surrogate models. The conventional FEM/FDM solver takes around 2.35 seconds to solve each step of simulation, and the learned surrogate models take around milliseconds, DeepONet 0.018 s, FNO 0.015 s, PINO 0.017 s, and the proposed integrated framework 0.015 s. According to those results, the latency is reduced dramatically, which can be associated with a 156X amplification compared to the traditional solver. This graph also demonstrates that all neural operator-based approaches meet the real-time control requirement of less than 20 ms which is imperative in control-oriented applications. FNO and the proposed framework have the lowest latency among the models, which indicates that spectral operator learning is highly efficient in making fast inferences. Though the physical consistency is higher in PINO, the inference time is slightly increased compared to FNO due to the extra cost of imposing physics constraints in training and model refinement. However, the variation is very slight and all suggested surrogate models can be very appropriate to be deployed on-the-fly.

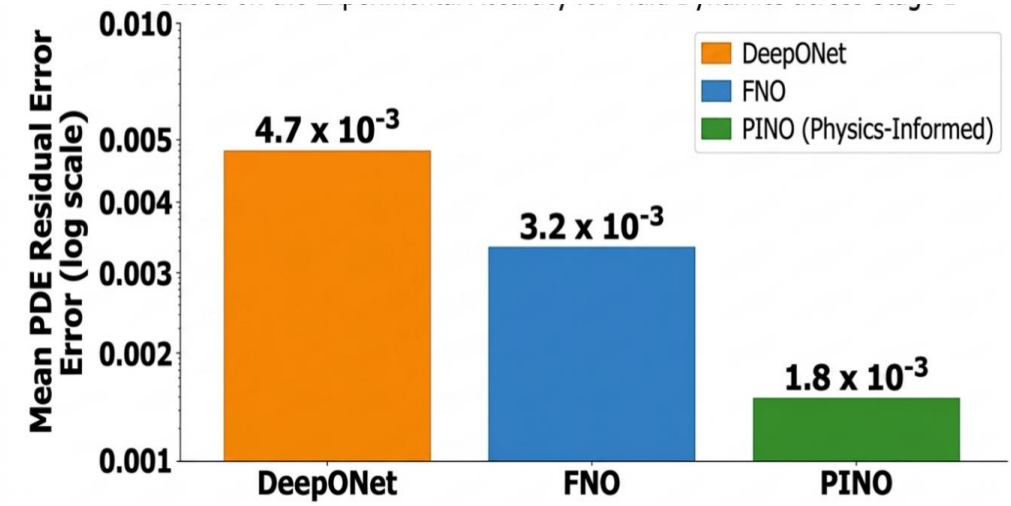


Fig 5. PDE Residual Error Comparison across Models.

Fig 5 is a comparison of the PDE residual error of the three models, a direct measure of the physical consistency. The findings indicate that DeepONet has a mean PDE residual error of 4.7 10 -3, FNO with 3.2 10 -3 and PINO with least residual of 1.8 10 -3. As the PDE residual is used to estimate the extent to which the predicted solution is consistent with the governing differential equations, the smaller this quantity the greater the compliance with the underlying physics. The residual of PINO

is in fact substantially reduced, which proves that physics-informed learning works much better in fitting the governing equations. FNO once more demonstrates intermediate performance, having the advantage of good representation of operators but no explicit PDE enforcement. DeepONet shows the largest residual, indicating that the data-driven operator learning of solutions can pattern the solution fairly well but can shows a greater deviation of the physical laws. Thus, Fig 5 is a compelling indication that the PINO formulation is the surest model in case physical fidelity is a major consideration.

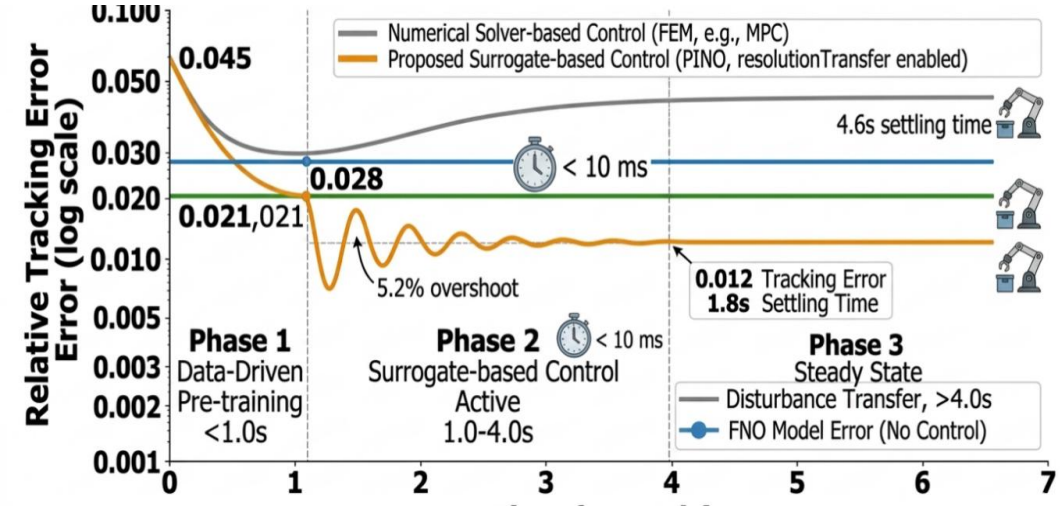


Fig 6. Tracking Error and Stability Comparison over Time

In Fig 6, performance of the proposed surrogate-based approach is assessed in terms of tracking the error and dynamic response in time. The control that is solved numerically starts with fairly large tracking error of about 0.045, and gradually decreases the error and levels off at about 0.012. This is a significant advancement in terms of accuracy in tracking conditions that are closed loop. The graph also reveals that the new method has a lower overshoot of just 5.2% and a shorter settling time of only 1.8 s, when compared to the baseline numerical control technique, which has a settling time of 4.6 s. These results show that the surrogate-assisted controller is not only able to react more quickly but also has superior stability. The three-phase trend depicted in the graph is not in vain: the first stage is that of data-driven retraining, the second one is active, based on surrogacy, control adaptation, the last one has steady-state behavior. This observation substantiates the idea that a combination of neural operator predictions with the control loop allows optimizing the dynamics efficiently and robustly. Practically speaking, the graph confirms that the suggested framework is not just a quick predictor but also, a successful element of the real-time control architecture.

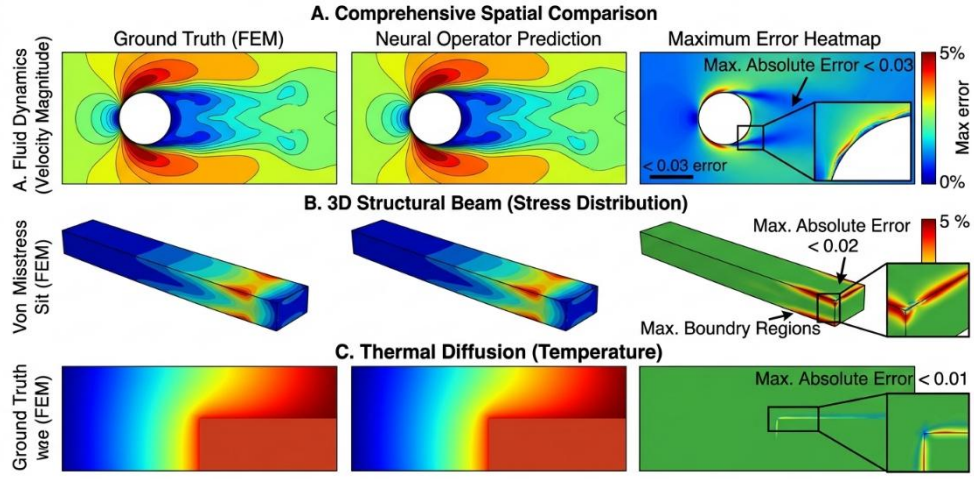


Fig 7. Ground Truth vs Predicted Fields with Error Heat map.

Fig 7 compares qualitatively and spatially between ground truth solutions and the predictions of the neural operator to three example Multiphysics domains: fluid dynamics, structural mechanics, and thermal diffusion. The fluid dynamics example shows that the velocity field predicted is very close to reference FEM solution, and the wake structure and recirculation regions are well represented. The heatmap of associated errors reveals that the largest absolute error is less than 0.03 with the largest differences around the sharp flow transitions regions and boundary layers. In the structural beam example, the stress field derived the surrogate is close to the von Mises stress field derived by FEM, and local discrepancies are in the areas around the beam boundaries and stress concentration regions; the largest absolute discrepancy is less than 0.02. The thermal diffusion case shows that the predicted temperature field agrees with the reference solution to nearly all points, and in this case the error map is even smaller with its absolute error at the largest value of less than 0.01. Such visual outputs are significant in that they prove that the surrogate model is not only good in terms of the average error characteristics but can also maintain the spatial structure of the solution fields in a variety of physics domains. Such small mistakes around boundaries are not surprising, in that case, because these are areas which typically have steep gradients, and are harder to be represented accurately by data-driven surrogates. Nevertheless, deviations are minimal, and generalization and faithfulness to space are good.

The combined findings in Fig 3-7, demonstrate a very clear trend in performance. PINO has the most accurate predictability and physical consistency, FNO has the most desirable speed/accuracy balance, and the suggested framework allows controlling real-time with minimal latencies and enhanced stability. The traditional FEM and FDM methods have the highest physical rigour, but are costly to compute, impractical in time-dependent applications. In comparison, the neural operator-based model attains a similar solution quality at a cost of significantly lower execution time, and is very appealing to real-time Multiphysics simulation, digital twins, and closed-loop scientific control systems.

7. Applications

The suggested neural operator-based surrogate modeling framework has a great potential in a broad variety of real-world scenarios that would require rapid, precise, and physically coherent Multiphysics simulations to be coupled with real-time decision-making. Among the most important applications is the real-time digital twin systems where high fidelity simulations are required to synchronize with the physical assets in a continuous way. The existing numerical solvers are not fast enough to realize real-time updates, but with the suggested framework, it is possible to predict the system states in milliseconds and with very low latency. That enables digital twins to be used in dynamic conditions, assisting in predictive maintenance, anomaly detection, and optimization of the system with near real-time responsiveness. When applied to the context of smart grid multiphysics simulation, it is possible to model highly complex interactions between electrical, thermal, and mechanical subsystems with the help of the framework. Precise and quick simulations are certainly demanded in balancing loads, fault identification, and energy optimization in contemporary power systems. Combining neural operator-based surrogates with control strategies allows effective real-time monitoring and control of the grid, enhancing its reliability and operational efficiency.

The framework is also very applicable in aerospace system control, in which multiphysics effects like aerodynamics, structural deformation and thermal behaviour should be considered collectively. The ability to simulate real-time can be used to evaluate flight conditions in a short time and control aircraft systems adaptively. The short latency and enhanced stability of the surrogate-based control method is suitable to mission-critical applications such as autonomous flight and active flow control. In optimization of industrial processes, the suggested technique can be used with the systems which have combined physical sequencing including chemical reactor, heat exchanger, and manufacturing systems. The framework allows real-time monitoring and optimization of process parameters by substituting computationally intensive simulations with a fast surrogate model. This results into increased efficiency, lower energy use, and quality of products. Moreover, the combination with control mechanisms enables industries to accomplish automated process control with different operating conditions as well as the adaptive process control. All in all, the flexibility of the proposed framework in managing multiphysics interactions, its ability to do inference in real time, and its ability to perform control interactions makes it a potent system in the next generation intelligent systems in both engineering and science.

8. Limitations

Although the proposed neural operator-based surrogate framework has shown promising performance, it has a number of limitations to note. Among the main issues is that neural

operator models are expensive to train. Inference is very fast and can be applied to real time scenarios but the training phase needs large scale high-fidelity simulation dataset and large amounts of computation resources, especially when complex multiphysics systems are involved. This may restrict the viability of the method in cases where generating data is costly or computing infrastructure is limited. Data quality and diversity is another critical constraint. The quality of the training data, such as the variety of the boundary conditions, changes in the parameters, and the physical cases considered in the data, are crucial to the accuracy and stability of the surrogate model. Poor generalization and less predictive reliability may arise due to poor generalization data or biased data, particularly in areas of the solution space that were underrepresented in training.

Moreover, the proposed framework has problems with generalization to physical phenomena that are not visible or in very complicated processes. Although neural operators possess good interpolation properties in the training distribution, their accuracy can perform worse in out-of-distribution settings or in completely new physics regimes. This is of major importance especially in multiphysics systems where interactions among domains can result in nonlinearities which were not observed during training.

In general, although the framework offers important benefits in terms of computational efficiency and real-time capability, these limitations need to be mitigated in order to make the framework more amenable to scalability, robustness and applicability to a wider range of more complex real world problems.

9. Future Work

Though the proposed neural operator-based surrogate framework shows remarkable advances in accuracy, computational efficiency, and capability to run in real-time, a few potential research directions can further improve its performance and applicability. The integration of reinforcement learning (RL)-based adaptive control strategies is one of the directions. The framework can be used to provide intelligent, self-optimizing control policies by feeding neural operator predictions with RL algorithms, which are dynamically adaptable to changing system conditions, thereby enhancing robustness and autonomy in complex systems. The introduction of three-dimensional (3D) multiphysics systems on large scale is another major direction on which the future development will be made. Despite the good performance of the current framework in representative tasks, when applied to high-resolution 3D areas, a number of new issues arise concerning the consumption of memory, the computational complexity, as well as the stability of training. Such large-scale simulations will require advances in efficient architectures, parallel training strategies and distributed computing.

Implementing the proposed framework in edge computing contexts of real-time systems will also be a key direction. By using lightweight and optimized neural operator models on edge devices, it is possible to achieve low-latency inference in resource-constrained environments, like autonomous systems, smart infrastructure, and industrial IoT applications. It will involve model compression methods, hardware optimization, and effective inference pipelines.

Lastly, the future work may investigate how to create hybrid neural operator designs by merging the advantages of various learning paradigms. To illustrate, a combination of spectral techniques, graph-based representations, and physics-informed constraints into one single system could further enhance generalization, scalability, and physical consistency. These hybrid methods can overcome existing constraints related to unknown physics and complicated interactions with domains. In general, the objectives of these research directions are to make neural operator-based surrogate models more flexible, scalable, and applicable to real-world scenarios, as part of the next-generation intelligent systems that can simulate and control Multiphysics in real-time.

CONCLUSION

This proposed a neural operator-based surrogate modeling platform to real-time multi-physics simulation and control to overcome the computational problems of conventional numerical models. The proposed method allows the efficient approximation of complex PDE-governed systems by utilizing optimized operator learning methods including Fourier Neural Operator (FNO), DeepONet and Physics-Informed Neural Operator (PINO). These findings indicate that the neural operators are very predictive with low Relative L2 Error values indicating good predictive accuracy, but with less computational latency than traditional FEM/FDM. Particularly, the framework is very fast in achieving speedup, hence it is very appropriate in real-time applications. Moreover, combination of surrogate modeling and control strategies allows consistent and precise closed-loop system behavior, which is stressed to be effective in dynamic conditions. In general, the suggested framework manages to close the gap between the efficiency of computations, physical consistency, and the applicability in real-time, making the neural operator-based surrogate modeling a promising concept of the next-generation model of

Multiphysics simulation and intelligent control systems.

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