A Physics-informed, Transfer Learning Approach to Structural Health Monitoring

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ABSTRACT

One of the main challenges for structural health monitoring (SHM) is a lack of failure data to make accurate health predictions. Obtaining desirable failure data is generally very expensive, given the required testing needed to measure all types of system failures, which may be unfeasible in many health monitoring applications. Machine learning has helped to improve health monitoring performance but is still limited by the availability, relevance, and quality of the training data. This data dependence impedes data-driven models from generalizing to unseen data, which is problematic for datasets lacking failure data. Physics-driven models, like finite-element models, are powerful tools for predicting structural responses when the governing physics are not clearly defined. These models can generate simulated fault data to address the data limitation without having to physically damage a structure, but are computationally expensive and susceptible to modeling errors that can prevent the data from being statistically comparable to experimental data.

A new trend has been to develop physics-guided machine learning models (PGML), a hybridization of the two aforementioned models that have been shown to improve generalization of, and even outperform, pure data-driven models while using less training data. These PGML models can take many forms, but generally embed some form of physics into a data-driven model as physically relevant constraints. Our research plan is to utilize PGML to improve neural network capabilities to predict structural damage. The proposed PGML model will follow a neural network architecture found in related literature consisting of feature extraction, physics-informed, and label prediction layers. The physics-informed layer will consist of an aggregate of sub-networks trained from simplified structure models which have known governing equations and can be used to generate simulated training data. The full PGML model will use transfer learning to bridge the connections between the untrained layers to the physics-informed layer using experimental data from more complex structures. We will verify our model using publically available SHM datasets used in a variety of past literature experiments.

1. PROBLEM STATEMENT

One of the main problems in any sort of prognostics-based study is having enough failure data [Bull, Worden, Manson, and Dervilis (2018); Gardner, Lord, and Barthorpe (2018); Fuentes, Cross, Gardner, Bull, Rogers, et al (2020)]. The large imbalance between "healthy" and "failure" data increases the difficulty for models to classify and/or localize damage, as well as the severity of damage. Desired damage states often have to be manually added to the host structure in order to accelerate the failure testing, since some structures require significant wear and tear before actual damage may occur "naturally". Testing using induced damage may not be feasible if the structure is still intended for use.

Structural health monitoring (SHM) is "any automated monitoring practice that seeks to assess the condition or health of a structure" [Fuentes et al. (2020)]. Structural health monitoring differs from other non-destructive testing/evaluation (NDT/NDE) techniques in that the sensors are permanently installed and the monitoring system is on-line performing continuous analysis [Fuentes et al. (2020)]. The primary questions an SHM system attempts to answer concern the existence, location, type, extent, and prognosis of damage in the system [Rytter (1993); Farrar & Worden (2012)]. Machine learning (ML) has become a popular method for answer these questions given its great ability of finding patterns within a large amount of data.

Two main types of SHM techniques include data-driven and physics-driven methods. Data-driven methods, such as ML, generally require a large amount of data in order to learn the statistically relevant relationship between input features and the structural health state. Generally speaking, the greater the representation of health states to structural responses within the data, the greater the reliability of the model. This is because a data-driven method can only make predictions from what it has seen from training data, making these models difficult to generalize to structures that do not respond the same as the training data, which can occur even for nominally identical structures [Fuentes et al (2020)]. Labeling the data is also difficult and/or costly to perform [Bull et al (2018)] and the existence of labels (or lack thereof) will determine whether the ML algorithm uses a supervised, unsupervised, or semi-supervised learning approach. These data-driven models are considered "black-box" models due to the decision-making process being relatively unintelligible to humans [Bull et al (2018); Cross, Gibson, Jones, Pitchforth, Zhang, and Rogers (2022)] and as such can hinder the confidence operators have with the model's predictions.

Physics-driven methods for SHM usually rely upon finite-element (FE) modeling and analysis to provide constrained data that is relevant to the observed structure. Two different analysis techniques using FE models include inverse model-driven methods and forward model-driven methods. Inverse model-driven methods update the FE model by comparing expected results to the actual measured results. However, this model updating may be ill conditioned since unique, stable solutions are not always feasible, and an adequate interpretation of these updated parameters may not be feasible when making a decision about the state of the structure [Fuentes et al (2020)]. An additional challenge to physics-driven methods is that fault mechanisms must be included in the FE model to obtain predicted fault response data, which fault mechanisms may not always be clearly defined and/or could result in predicted fault response data that does not match measured data.

Forward model-driven SHM techniques use the FE model to generate a training dataset from operational conditions that are used in a supervised learning approach in an attempt to build machine-learning models and address the problem of not having sufficient fault data [Fuentes et al (2020); Gardner et al (2018); and Balthorpe (2010)]. However, these methods require that the generated dataset give statistically significant results that are consistent with measurements obtained from the actual structure, and require calibration and verification from real world data, which may not be feasible [Fuentes et al (2020)].

Additional challenges with FE models include inherent modeling discrepancies due to structural complexity or lack of knowledge about certain material properties that may be simplified to perform the desired analysis [Farrar & Worden (2012); Ozdagli & Koutsoukos (2021)]. Another challenge is computational expense [Gardner et al (2018)] as well as efficiency from high fidelity models due to having a large number of parameters required to build the model [Fuentes et al (2020)].

A new on-going research strategy is developing hybrid-based models that use both data-driven and physics-driven methods to overcome their respective challenges. Physics-informed machine learning (PIML), or physics-guided machine learning (PGML), is a hybrid modeling approach that has become increasingly popular since its initial online publication dating back to 2016 (see Figure 1). Karniadakis, Kevrekidis, Lu, Perdikaris, Wang, and Yang (2021) define PIML as a method that "integrates seamlessly data and mathematical physics models, even in partially understood, uncertain and high-dimensional contexts." The purpose for using a physics-informed model is to better constrain how a data-driven model learns from the data by teaching it known information about the system being analyzed [Zhang, Liu, and Sun (2020a)]. Known advantages for using PIML include a lower training cost [Yu, Yao, and Liu (2020)], requires less training data, [Zhang et al (2020a), Zhang, Liu, and Sun (2020b)], has improved generalizability [Zhang et al (2020a); Yu et al (2020)], and generally outperforms data-driven models [Yu et al (2020); Zhang et al (2020b)]. The added physics to data-driven models makes them gray-box models, which improves the human interpretability and confidence in the model's predictions.

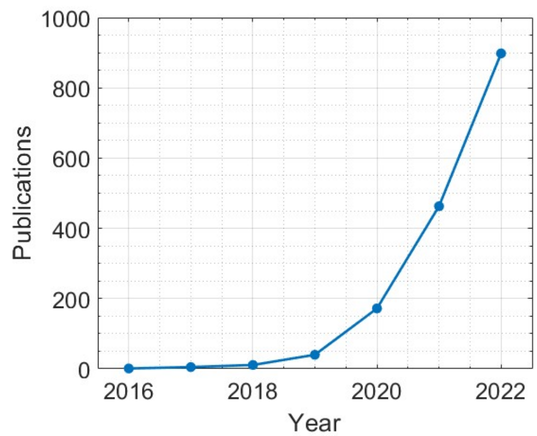

Figure 1. Number of publications (title and abstract) on "physics informed machine learning" or "physics informed neural networks" from 2016 to 2022 (Source: app.dimensions.ai)

2. NOVEL CONTRIBUTIONS

Many of the PGML methods within SHM make use of FE models to either generate simulated data for different damage states or perform model updating to compare predicted results with measured results for anomaly detection. However, FE models are generally computationally expensive that increases with the complexity of the model. Additionally, FE models can have intrinsic modeling discrepancies (say from not knowing the exact material properties for the model) which can similarly result in differences between the simulated and experimental data [Ozdagli & Koutsoukos (2021)]. While PGML has been shown to improve generalization even when a FE model has known modeling errors [see Ozdagli & Koutsoukos (2021)], the question remains can you still get comparable results without the need for a computationally expensive FE model?

The reason complex FE models are used in SHM is because the physics for a complex structure may not be well-defined or intrinsically deterministic (i.e., an ODE/PDE is not defined). However, the individual components that make up the structure have more defined physics that when put together may form a closer approximation to the ground truth. We hope to use PGML models to act as surrogate FE models at the individual structural component level, where the physics are more clearly defined. The model would initially consist of neural network layers trained for simple structural components using PGML. Then, through the principle of transfer learning, we can model a more complex structure by building a neural networked that aggregates these physics-trained layers. We expect this will improve the generalizability of SHM models while using less training data and without a complex FE model. This trained PGML is not expected to take the place of a FE model, but should ideally be compatible with complex FE models for determining the health of a structure.

3. PROPOSED RESEARCH PLAN

Our proposed research plan is to iteratively build a physics-informed neural network (see Figure 2) that can model increasingly complex structures by:

a) individually training a collection of independent physics-informed networks using simplified physics-based models to generate their respective training data,

b) aggregating the trained physics-informed sub-networks to form a single, physic-informed layer as part of a larger neural network, and

c) using transfer learning to train and connect neural network layers around the physics-informed layer using data from the complex physical structure.

The physics-informed sub-networks can be trained individually using simulated data derived from their respective physics-based model(s) and can be verified using appropriate experimental data (when available). The individual performance of the sub-networks will be evaluated using both physics-guided neural networks and physics-agnostic (i.e., purely data-driven, or vanilla) neural networks to test the validity of using PGML methods with their expected benefits. Additionally, we will evaluate how much simulated data is required for accurate performance for each sub-network, and gauge how that performance scales when linked to more complex networks, where the physics is not so clearly defined. It is expected that the physics-informed layer (i.e., the aggregated trained physics-informed sub-networks) is sufficient to evaluate simple structures with clearly defined physics (e.g., ODEs/PDEs, equations of motion, etc.).

To model more complicated structures where the physics are not so clearly defined, we will add neural network layers around this physics-informed layer, where the layers

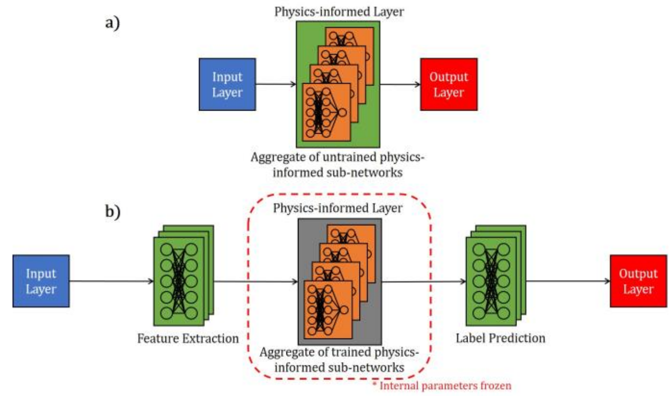

Figure 2. Proposed physics-guided machine learning model architecture for a) training and aggregating physics-informed neural networks from simplified physical systems and b) performing transfer learning with the pre-trained physics-informed layer to train a model for a more complex physical structure.

preceding the physics-informed layer act as feature extractors and the layers following act as health label predictors (see Figure 2b). This model architecture was implemented by Ozdagli & Koutsoukos (2021) and showed promising results, with the difference being their implementation used outputs from a FE model to act as the physics-informed layer instead of our proposed collection of sub-networks. The new model will be trained using data collected from the complex structure in the form of transfer learning to bridge the connections between the added layers and the physics-informed layer. The term "transfer learning" within the context of this study means the process of connecting new, untrained model layers to pre-trained model layers (i.e., connecting the known with the unknown).

Freezing the pre-trained layers' parameters during the training process reduces the model's overall number of parameters that need to be trained for the complex structure. This process provides the added benefit of reducing the total number of trainable parameters for a potentially deep network, preventing the need to train a blank network of equal size and depth. This model type also allows for models to be built incrementally for increasing complex structures, starting from an elemental level, to a structural sub-element level, to then a full structural element. These tiers of models may then serve as physics-informed building blocks for other structures that may contain similar structural components.

To get relevant experimental data, a number of datasets related to SHM are available online, each ranging in different structural complexity and measurements. Some examples include datasets from the Los Alamos National Laboratory

SHM Data Sets and Software website containing vibration data for vibration-based SHM approaches. We plan to also make extended measurements for a more complex structure (e.g., hydro-turbine blade) starting with a coupon test, then graduating to a substructure testing, and eventually a full-scale structure test.

For future work, a FE model could additionally be used to generate training data from increasingly complex structures as part of the transfer learning process. This would allow for a FE model to still be used with this neural network architecture that may potentially improve the transfer learning training process. Additional benefits would need to be explored.

REFERENCES

Barthorpe, R. J., (2010). *On model- and data-based approaches to structural health monitoring.* PhD thesis, University of Sheffield.

Bull, L., Worden, K., Manson, G., & Dervilis, N. (2018). Active learning for semi-supervised structural health monitoring. *Journal of Sound and Vibration, 437,* 373-388.

Cross, E. J., Gibson, S. J., Jones, M. R., Pitchforth, D. J., Zhang, S., & Rogers, T. J. (2022). Physics-informed machine learning for structural health monitoring. *Structural Health Monitoring Based on Data Science Techniques*, 347-367.

Farrar, C. R., & Worden, K. (2012). *Structural health monitoring: a machine learning perspective.* John Wiley & Sons.

Fuentes, R., Cross, E. J., Gardner, P. A., Bull, L. A., Rogers, T. J., Barthorpe, R. J., … & Worden, K. (2020). Structural Health Monitoring and Damage Identification. *Handbook of Experimental Structural Dynamics*, 1-72.

Gardner, P., Lord, C., & Barthorpe, R. (2018). A probabilistic framework for forward model-driven SHM. In *Proceedings of the 9th European Workshop on Structural Health Monitoring (EWSHM 2018)*, (Nov. 11), NDT.net.

Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., & Yang, L. (2021). Physics-informed machine learning. *Nature Reviews Physics*, *3*(6), 422-440.

Los Alamos National Laboratory. *SHM Data Sets and Software*, www.lanl.gov/projects/national-security-education-center/engineering/software/shm-data-sets-and-software.php.

Ozdagli, A. I., & Koutsoukos, X. (2021). Model-based damage detection through physics guided learning. In *Annual Conference of the PHM Society* (Vol. 13, No. 1).

Rytter, A., (1993). *Vibrational based inspection of civil engineering structures*. PhD thesis, Department of Building Technology and Structural Engineering, Aalborg University.

Yu, Y., Yao, H., & Liu, Y. (2020). Structural dynamics simulation using a novel physics-guided machine learning method. *Engineering Applications of Artificial Intelligence*, *96*, 103947.

Zhang R., Liu, Y., & Sun, H. (2020a). Physics-guided convolutional neural network (PhyCNN) for data-driven seismic response modeling. *Engineering Structures*, *215*, 110704.

Zhang, R., Liu, Y., & Sun, H. (2020b). Physics-informed multi-LSTM networks for metamodeling of nonlinear structures. *Computer Methods in Applied Mechanics and Engineering*, *369*, 113226.