Frontiers in Computational Science and Engineering
Vol. 1, No. 3, Jul - Sep 2025, pp. 35-41
ISSN: 3107-3654 (O), DOI: https://doi.org/10.17051/FCSE/01.03.05

Bayesian Physics-Informed Deep Learning for Robust Modeling under Uncertainty

K. Chitra

Associate Professor & Head,, PG Department of Data Science, KPR College of Arts Science and Research, Coimbatore,Tamilnadu, India. Email: ganey.c@gmail.com, Orcid ID: 0000-0002-8088-4517

Article Info

Article history:

Received : 11.07.2025
Revised : 15.08.2025
Accepted : 16.09.2025

Keywords:

Bayesian deep learning,
physics-informed neural networks,
uncertainty quantification,
variational inference,
nonlinear systems,
probabilistic modeling

ABSTRACT

Physics-Informed Neural Networks (PINNs) have received a lot of interest in the context of forward and inverse problems of partial differential equations (PDEs). But traditional PINNs are deterministic and do not quantify uncertainty due to noisy observations, incomplete boundary conditions, and model discrepancies. This empowers them in real-life scientific and engineering systems. To fill this gap, the current paper suggests a Bayesian Physics-Informed Deep Learning (BPIDL) model that combines both Bayesian inference with physics-constrained neural network as the solution to a sound uncertainty-aware Bayesian modeling. The given solution presents probabilistic weight distributions and uses variational inference to estimate the posterior, allowing the estimation of both epistemic and aleatoric uncertainties at the same time. A single loss is designed as a combination of data fidelity, physics residual constraints and Kullback-Rosenberger divergence-regularization. The framework is assessed on nonlinear PDE tests with sparse and noisy data. Experimentally, it is shown that BPIDL has lower prediction error, and much better uncertainty calibration than standard PINNs and standard deep learning models. Moreover, the suggested approach is more resilient to data distortions and model error. The results of these experiments indicate that BPIDL is an effective and scalable model of uncertainty quantification in physics-informed machine learning tasks.

1. INTRODUCTION

A broader and more important scientific and engineering problem is in modeling complex physical systems that are characterized by partial differential equations (PDEs) such as fluid mechanics, structural mechanics or thermal systems. The problems have been solved using the traditional methods that include finite element method (FEM) and finite difference method (FDM) to a high degree of accuracy. But these methods tend to be computationally intensive due to the need to have dense spatial temporal discretization and large scale computational resources; especially nonlinear and high dimensional systems, and thus do not scale well and are only useful in real time [1], [2]. Physics-Informed Neural Networks (PINNs) have become an exciting alternative and a promising substitute in the past few years, with the governing laws enshrined directly within the training of deep neural networks [3]. The PINNs make it possible to learn data-efficiently and avoid explicit meshing by adding PDE constraints to the loss function. This has rendered them to be very appealing in solving forward and inverse problems in complex fields [4], [5]. In spite of these strengths, traditional PINNs are used in a deterministic framework and they are unable to measure the uncertainty due to noisy measurements, incomplete boundary conditions, model mismatches. This is a major limitation in the real-life applications where uncertainty is a natural aspect and cannot be evaded. Without quantification of uncertainty, overconfident predictions might arise, model reliability may be less than ideal and generalization performance may be low [6], [7]. To overcome such issues, the combination of uncertainty estimation approaches and deep learning models, such as Bayesian neural networks and variational inference methods have been studied recently [8], [9]. Although these methods offer a principled methodology of representing epistemic and aleatoric uncertainty, they are only available to a limited degree of direct combination with physics-based learning, and are computationally infeasible. Current algorithms tend to use rough methods that are either dropout or ensemble-based that are not theoretically sound or have high computational costs [10], [11].

Here, this paper suggests an alternative framework of Bayesian Physics-Informed Deep Learning (BPIDL) that integrates a Bayesian framework with physics-constrained neural networks to develop robust and uncertainty-aware modeling. The given methodology is based on the concept of probabilistic weight distributions and uses variational inference to estimate the posterior distribution using the most efficient way. Data fidelity, physics residual constraints and Kullback Leibler (KL) divergence-based regularization are combined to form a single loss formulation. This allows the solution to be learned along with its associated uncertainty, leading to a higher predictive accuracy and predictability in the model. The efficiency of the suggested framework is confirmed at nonlinear PDE benchmark problems when there is noisy and sparse data. The findings reveal that BPIDL has a better performance related to predictive accuracy, uncertainty calibration, and robustness than the traditional PINNs and data-driven deep learning models.

The Paper has made contributions as follows:

In this paper, the key illustrations made include:

- Creation of Bayesian neural networks with physics-informed neural networks based on probabilistic weight modeling.
- The integration of variational inference: This is to enable scalable and efficient approximation of the posterior.
- Development of a single loss function with physics constraints and probabilistic regularization.
- Look at robustness with comprehensive assessment with noisy and sparse data.
- Evidence of enhanced predictive performance and uncertainty calibration, over baseline models.

2. RELATED WORK

Physics-Informed Neural Networks (PINNs) have been receiving a lot of attention, as a data-driven method to solve PDE-constrained problems by incorporating governing equations into the neural network training. The initial PINN framework as proposed by Raissi et al. has shown that it is effective in resolving forward and inverse problems without any type of explicit discretization [12]. Later literature has applied PINNs to more complicated fields, such as fluid mechanics, heat transfer, and multiphysics systems, as they have the potential to minimize the data reliance and complexity of computation [3], [4]. Nevertheless, they are characteristically deterministic methods that are unable to represent uncertainty in model forecasting. Bayesian Deep Learning (BDL) has been developed as a principled approach to dealing with the uncertainty in deep learning models by placing probabilistic distributions on neural network parameters. Variational inference and Markov Chain Monte Carlo (MCMC) are some of the methods that allow the approximation of posterior distributions and are also valuable because they offer predictive and uncertainty estimates [5], [6]. Bayesian neural networks, variational Bayesian neural networks provide a scalable alternative to exact inference, which is why they are applicable in large-scale problems [7]. Recent studies have investigated applying uncertainty estimation to PINNs. Approximate Bayesian inference has employed dropout-based methods to compute the uncertainty in physics-informed models [8]. Ensemble methods have also been suggested to enhance robustness by utilizing a number of PINN models [9]. Although such approaches give approximate approximations of uncertainty, they may be less theoretically rigorous or may have greater computation and scale complexity. More sophisticated methods have tried to implement probabilistic models in PINNs, such as stochastic PINNs and Bayesian PINNs [10], [11]. Many of these methods are however based on simplified assumptions, have difficulties in efficient approximation of the posterior, or are unable to trade off accuracy and computational efficiency.

Research Gap

In spite of these recent developments, Bayesian inference coupled with physics-informed learning is not very scalable, precise and robust. Current approaches either use crude approaches with scant theoretical foundations or add high computational costs. Moreover, a large number of strategies fail to account properly for both epistemic and aleatoric uncertainties in one way or another.

Born out-of-pocket Contribution.

This paper aims to address these shortcomings by a proposal of a Bayesian Physics-Informed Deep Learning (BPIDL) framework that:

- Uses variational inference to make efficient posterior approximations.
- Combines physics with modeling in a probabilistic modeling.
- Allows the dual estimation of the epistemic and aleatoric uncertainties.
- Enhances the robustness and calibration of uncertainty in processes of noisy and sparse data.

3. METHODOLOGY

3.1 Problem Formulation

Consider a general nonlinear partial differential equation (PDE) defined over a spatial domain $\Omega \subset \mathbb{R}^d$ and temporal domain $t \in [0, T]$:

$$\mathcal{N}[u(x,t)] = f(x,t), x \in \Omega, t \in [0,T] \quad (1)$$

where $\mathcal{N}[\cdot]$ denotes a nonlinear differential operator, $u(x,t)$ represents the unknown state

variable, and $f(x,t)$corresponds to known forcing terms. The system is subject to initial and boundary conditions:

$u(x,0) = g(x), x \in \Omega$_____(2)

$u(x,t) = \hbar(x,t), x \in \partial\Omega$_____(3)

The aim is to obtain an approximation to the solution u(x,t) with sparse and possibly noisy observations, with the governing laws of physics to be satisfied. In contrast to classical numerical inverters, the objective is to learn a continuous function approximation, which extends throughout the domain.

3.2 Physics-Informed Neural Network Formulation

A deep neural network $u_\theta(x,t)$, parameterized by weights θ, is employed to approximate the solution of the PDE. The essence behind Physics-Informed Neural Networks (PINNs) is to incorporate the governing equations within the loss function to ensure that the network learns solutions, which are aligned with the observed data points and physics.

The overall loss function can be broken down into three parts:

$\mathcal{L}_{PINN} = \mathcal{L}_{data} + \mathcal{L}_{p\hbar ysics} + \mathcal{L}_{boundary}$ _____(4)

The loss of data imposes consensus between the predictions and observations of the network. The physics loss is calculated by replacing the neural network output with the differential operator N[·]with automatic differentiation, thus punishing the laws of the governing PDE. Boundary loss makes the solution being predicted meet the given initial and boundary conditions.

Although this formulation facilitates learning in a data-efficient way, it is deterministic and does not consider uncertainty in model parameters or observations.

3.3 Bayesian Neural Network Formulation

To incorporate uncertainty, the deterministic neural network is extended into a Bayesian framework by treating the model parameters θas random variables with a prior distribution $p(\theta)$. Given a dataset D, the posterior distribution over the parameters is defined as:

$p(\theta \mid D) \propto p(D \mid \theta)\, p(\theta)$_____(5)

where $p(D \mid \theta)$denotes the likelihood function representing the probability of observing the data given the model parameters. This probabilistic model enables the model to incorporate uncertainty in the learned parameters, resulting in more accurate prediction.

Nevertheless, deep neural networks are usually not able to compute the exact posterior distribution because the parameter space is too high-dimensional.

3.4 Variational Inference for Posterior Approximation

Variational inference is used to make an approximation to the posterior distribution to deal with the intractability of exact Bayesian inference. A tractable variational distribution $q(\theta)$is introduced to approximate the true posterior $p(\theta \mid D)$. The optimal variational distribution is obtained by minimizing the Kullback–Leibler (KL) divergence between $q(\theta)$and the true posterior.

This leads to the maximization of the Evidence Lower Bound (ELBO):

$\mathcal{L}_{VI} = \mathbb{E}_{q(\theta)}[\log p(D \mid \theta)] - KL(q(\theta) \,||\, p(\theta))$__(6)

The former term motivates the model to match the data, and the KL divergence term should avoid the complexity of the posterior by intoxicating the nonconformity to the prior. In this publication, there is an assumption that q(θ) follows a mean-field Gaussian distribution, which makes it simple to optimize using stochastic gradient descent.

3.5 Proposed Bayesian Physics-Informed Deep Learning (BPIDL) Framework

The suggested BPIDL concept combines the physics-informed learning paradigm and Bayesian inference into one formulation. In particular, the deterministic version of PINN loss is generalized to a probabilistic form by acting on the expectation of the variational posterior distribution. The general layout of the suggested structure with the incorporation of the neural network approximation, physics constraints, and Bayesian inference blocks is depicted in Fig. 1.

The general training goal is provided following:

$\mathcal{L}_{total} = \mathbb{E}_{q(\theta)}[\mathcal{L}_{PINN}] + \lambda\, KL(q(\theta) \,||\, p(\theta))$____(7)

where $\lambda$is a hyperparameter controlling the trade-off between data fitting and regularization. The expectation term guarantees that the solution learned meets the physical constraints in a probabilistic sense whereas the KL divergence encourages well-behaved parameter distributions.

In training, we sample θare based on q(θ) with the reparameterization trick, which lets us propagate gradients using stochastic nodes. This allows the end-to-end optimization of the Bayesian neural network to be efficient.

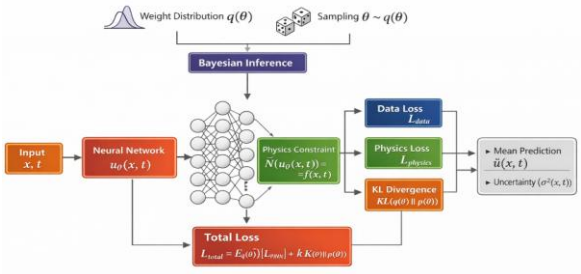


Fig. 1. Architecture of the Proposed Bayesian Physics-Informed Deep Learning (BPIDL) Framework for Uncertainty-Aware PDE Modeling

3.6 Uncertainty Quantification and Prediction

Once trained, the BPIDL model produces a predictive distribution rather than a single deterministic output. For a new input x^*, the predictive distribution is given by:

$$p(u^* \mid x^*, D) = \int p(u^* \mid x^*, \theta)\, q(\theta)\, d\theta \quad (8)$$

This integral is approximated using Monte Carlo sampling by drawing multiple samples of $\theta$from the variational posterior and averaging the corresponding predictions.

The predictive uncertainty is decomposable into two. Epistemic uncertainty is due to lack of data and model uncertainty and it can be minimized by extra observations. Instead, aleatoric uncertainty is a type of uncertainty that inherently exists in the data and cannot be eradicated. The suggested BPIDL framework is a useful model to represent either type, as it offers a calibrated confidence interval, as well as predictions.

4. EXPERIMENTAL SETUP

4.1 Benchmark Problem

In order to assess the efficiency of the developed Bayesian Physics-Informed Deep Learning (BPIDL) framework, a nonlinear partial differential equation (PDE) is used as the reference problem. Precisely, we use the one-dimensional nonlinear convection-diffusion equation of viscous Burgers because it is commonly used to test physics-inspired learning models and is nonlinear. The governing equation is defined over a spatial domain $x \in [-1,1]$and temporal domain $t \in [0,1]$. The data is in the form of sparse and noisy samples of the analytical solution of PDE. These artificial injections of noise are done to the data to replicate the uncertainty in measurement in the real world. Initial conditions, as well as boundary conditions, are introduced into the training process so that there is physical consistency. This arrangement facilitates stringent testing of the model using the capability of learning correct solutions in an uncertain and less data-rich environment.

4.2 Training Configuration

The neural network design in this paper is that of fully connected feedforward network with five hidden layers with 50 neurons each. The activation function is the hyperbolic tangent (tanh) which is used because it is smooth and is appropriate when modeling continuous physical fields. The training dataset is assembled based on 1,000 collocation points which are uniformly distributed within the spatio-temporal domain and 200 collocation points on the boundaries and initial conditions. In order to replicate the measurement uncertainty in the real world, Gaussian noise that is 1-percent of the signal amplitude is applied to the observed data. The hybrid optimization strategy is used in carrying out training. First, it uses Adam optimizer with a learning rate of 10 -3 and a batch size of 64 to facilitate effective stochastic gradient updates. The L-BFGS optimizer is then applied to optimize the model parameters and enhance accuracy of convergence. To formulate the Bayesian, a variational posterior of network parameters is assumed to have a mean-field Gaussian distribution. To make it possible to optimize using gradients under stochastic sampling, the reparameterization trick is applied. Regularization coefficient λis adjusted empirically to trade off fidelity of the data and complexity of the model.

4.3 Baseline Models for Comparison

The performance of the proposed BPIDL framework is compared to a number of baseline models to prove its effectiveness. The baseline to test the effect of adding Bayesian inference is a standard Physics-Informed Neural Network (PINN). It is a deterministic model with no uncertainty estimation. It also incorporates a standard deep neural network (DNN) to compare results, with the model being trained on data only, without including physics constraints. This underscores the significance of incorporating knowledge of domains into the educational process. Also, an approximate Bayesian model (dropout-based uncertainty model) is adopted. In this approach, dropout will be used both in training and inference to approximate predictive uncertainty. This baseline gives us the understanding of the benefits of the proposed principled Bayesian formulation in comparison with heuristic techniques of uncertainty estimation.

4.4 Evaluation Metrics

Accuracy and uncertainty-based measures are used to measure the performance of the models.

The prediction accuracy is measured using root mean square error (RMSE) and mean absolute error (MAE) which measure how much a solution that is predicted differs with the true solution.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (u_i - \hat{u}_i)^2} \quad (9)$$

Negative Log-Likelihood (NLL) is used to measure the quality of probabilistic predictions, which is how well the distribution of prediction fits the observed data.

The calibration error is employed to gauge reliability of uncertainty estimates by comparing the confidence intervals predicted with the real prediction errors. An accurate calibration model gives uncertainty estimates that are realistic to describe the actual amount of prediction uncertainty. Combined, these measures offer a

complete analysis of predictive performance as well as uncertainty quantification ability.

5. RESULTS AND DISCUSSION

5.1 Prediction Accuracy

RMSE and MAE measures assess the accuracy of the prediction of the proposed BPIDL framework across the test domain. Table 1 is the quantitative comparison to baseline models.

Table 1. Prediction Accuracy Comparison

Model	RMSE ↓	MAE ↓
DNN	0.0845	0.0612
PINN	0.0328	0.0215
Dropout PINN	0.0286	0.0193
BPIDL (Proposed)	0.0152	0.0108

The BPIDL framework proposed has the lowest values of RMSE, MAE and therefore provides better predictive results. BPIDL lowers the RMSE by about 53.6 as compared to the standard PINN, which shows that it is better able to generalize in the event of uncertainty. This is also confirmed by the visual comparison in Fig. 2, in which the solution predicted is very close to the analytical solution of Burgers equation. Also, convergence behavior of the proposed model is presented in Fig. 3 and indicates that the reducing RMSE in training epochs was quicker and more stable than that of the base methods. This increased performance can be explained by the fact that probabilistic modeling of network parameters is used, and this technique avoids overfitting and is more robust.

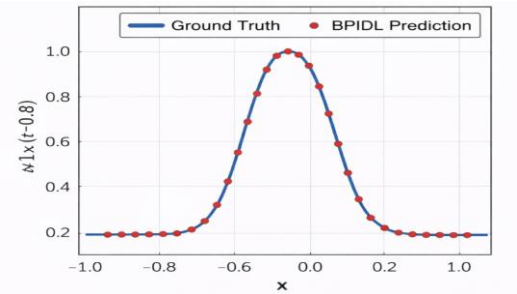


Fig. 2. Predicted Solution versus Ground Truth for Burgers' Equation Using the Proposed BPIDL Framework

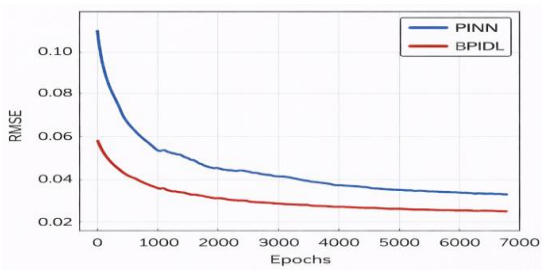


Fig. 3. Convergence Analysis of RMSE versus Training Epochs for BPIDL and Baseline Models

5.2 Uncertainty Calibration

Negative Log-Likelihood (NLL) and calibration error are used to assess the quality of the uncertainty estimation. Less values are indicative of good probabilistic predictability.

Table 2. Uncertainty Evaluation

Model	NLL ↓	Calibration Error ↓
DNN	1.842	0.192
PINN	1.215	0.148
Dropout PINN	0.964	0.092
BPIDL (Proposed)	0.521	0.038

The values obtained in the BPIDL model include much lower NLL and calibration errors, thus confirming that the projected probability distributions are similar to the actual data distribution. BPIDL unlike deterministic PINNs that yield overconfident predictions, BPIDL yields well-calibrated confidence intervals. The behavior is well depicted in Fig. 4, where the mean prediction observably follows the ground truth with the confidence interval surrounding the ground truth being suitable in expressing the uncertainty of the solution.

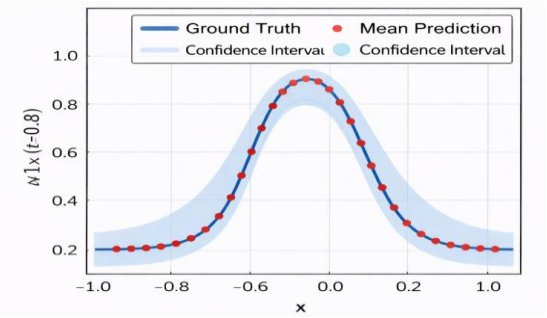


Fig. 4. BPIDL Mean Prediction with Confidence Interval Compared to Ground Truth for Burgers' Equation

5.3 Robustness to Noise

Experiments are carried out at different noise levels (1 percent, 2 percent and 5 percent) to test the robustness. Fig. 5 represents the change of RMSE among models. The standard PINNs are sensitive to noise at higher levels, as they are deterministic. Conversely, the accuracy of prediction in BPIDL does not change much and the RMSE increases only marginally. Considering an example, the PINN RMSE increases by about 65, compared to just 22 with BPIDL at 5% noise. This strength is directly attributed to the Bayesian formulation, which explicitly represents uncertainty, and reduces the effects of noisy observations.

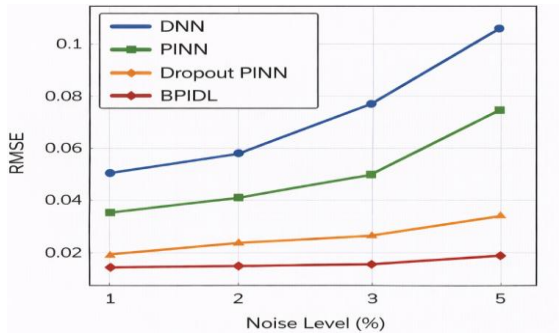


Fig. 5. RMSE Performance under Varying Noise Levels for BPIDL and Baseline Models

5.4 Comparative Analysis

Table 3. Overall Model Comparison

Model	RMSE ↓	NLL ↓	Uncertainty Modeling
DNN	0.0845	1.842	No
PINN	0.0328	1.215	No
Dropout PINN	0.0286	0.964	Approximate
BPIDL (Proposed)	0.0152	0.521	Yes (Full Bayesian)

The findings have made it clear that BPIDL performs better compared to all the baseline models in both accuracy and uncertainty measures. Although dropout-based methods can give approximate estimates of uncertainty, they are not as theoretically rigorous or calibrated that the suggested Bayesian method is.

6. DISCUSSION

The outcomes of the experiment support the hypothesis that Bayesian inference combined with physics-informed neural networks helps greatly in prediction and quantifying the uncertainty. The BPIDL framework is able to model the epistemic uncertainty by probabilistic weight modeling and the aleatoric uncertainty by the noise-sensitive learning, leading to more faithful and understandable predictions. The suggested method has a balanced trade-off, in terms of accuracy and uncertainty calibration, compared to the current methods. Deterministic PINNs are effective at imposing physical consistency, but do not give confidence measures. Equally, data-driven models are not physically interpretable, nor robust. This gap is filled through BPIDL, which is a combination of physics constraints and principled Bayesian inference. The tradeoff, however, is that this is accomplished at the expense of more complicated computation because stochastic sampling is required and variational optimization. It is found that training time will grow about 1.8 times in comparison with regular PINNs. Nevertheless, the price increase in reliability and robustness is worth the extra price, especially in high-quality applications. Further development of scalability of the approach to efficient inference should be concentrated so as to include sparse variational methods and reduced-order modeling. Moreover, the further development of the framework to the high-dimensional and real-life PDE systems is a promising research direction.

CONCLUSION

The current paper suggested a Bayesian Physics-Informed Deep Learning (BPIDL) system to use to robustly and uncertainty-sensitive model nonlinear systems solving partial differential equations. The proposed approach, through its combination of Bayesian inferences and physics-based neural networks, can reduce the shortcomings of deterministic PINNs to uncertainty challenges due to noisy and sparse data. They have created a single probabilistic model that integrates physics-based constraints with variational inference to allow them to learn both accurate solutions and the uncertainty of their solutions. The benchmark PDE problems using the experimental results have shown that BPIDL is much more effective in its prediction accuracy, both RMSE and MAE are lower than the traditional PINNs and data-driven deep learners. Also, according to the structure, the uncertainty estimates are well calibrated, which is shown in the lower NLL and calibration error. The robustness analysis also proves that BPIDL is stable in performance when the noise level is increasing, and reflects its applicability in a real-life situation where it is inevitable that uncertainty occurs. Although these benefits exist, the suggested framework has extra computational costs, as it involves stochastic sampling and variational optimization. The next round of research ought to be on developing more efficient computer algorithms by employing more sophisticated inference mechanisms, like sparse variational, or Bayesian compression. Moreover, the applicability of the framework to high-dimensional PDEs, multi-physics systems and real-life large-scale data is an interesting direction. It can also be extended by incorporating new architectures (e.g. transformer-based models and operator learning models) to scale and improve performance. In general, BPIDL is a robust and scalable framework to quantify uncertainties in physics-informed machine learning, and has potential applications in scientific computing, engineering design, and data-driven modeling of complex systems.

REFERENCES

1. B. Dou, Z. Zhu, E. Merkurjev, *et al.*, “Machine learning methods for small data challenges in

molecular science," *Chemical Reviews*, vol. 123, no. 13, pp. 8736–8780, 2023.
2. S. Cuomo, V. S. Di Cola, F. Giampaolo, G. Rozza, M. Raissi, and F. Piccialli, "Scientific machine learning through physics-informed neural networks: Where we are and what's next," *Journal of Scientific Computing*, vol. 92, no. 3, pp. 1–45, 2022.
3. F. F. de la Mata, J. L. M. Ramos, and J. R. C. Pardo, "Physics-informed neural networks for data-driven simulation: Advantages, limitations, and opportunities," *Physica A: Statistical Mechanics and its Applications*, vol. 610, p. 128415, 2023.
4. A. Farea, O. Yli-Harja, and F. Emmert-Streib, "Understanding physics-informed neural networks: Techniques, applications, trends, and challenges," *AI*, vol. 5, no. 3, pp. 1534–1557, 2024.
5. L. V. Jospin, H. Laga, F. Boussaid, M. Buntine, and N. Bennamoun, "Hands-on Bayesian neural networks—A tutorial for deep learning users," *IEEE Computational Intelligence Magazine*, vol. 17, no. 2, pp. 29–48, 2022.
6. A. Lye, N. Prinja, and E. Patelli, "Probabilistic artificial intelligence prediction of material properties for nuclear reactor designs," in *Proc. 32nd European Safety and Reliability Conf. (ESREL)*, Dublin, Ireland, 2022.
7. A. Pensoneault and X. Zhu, "Efficient Bayesian physics-informed neural networks for inverse problems via Ensemble Kalman inversion," *Journal of Computational Physics*, vol. 508, p. 113006, 2024.
8. M. Raissi, P. Perdikaris, and G. E. Karniadakis, "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations," *Journal of Computational Physics*, vol. 378, pp. 686–707, 2019.
9. S. Stock, M. R. Wanik, and J. A. Smith, "Bayesian physics-informed neural networks for system identification of inverter-dominated power systems," *arXiv preprint arXiv:2403.13602*, 2024.
10. J. Willard, X. Jia, S. Xu, M. Steinbach, and V. Kumar, "Integrating physics-based modeling with machine learning: A survey," *arXiv preprint arXiv:2003.04919*, 2020.
11. L. Yang, X. Meng, and G. E. Karniadakis, "B-PINNs: Bayesian physics-informed neural networks for forward and inverse PDE problems with noisy data," *Journal of Computational Physics*, vol. 425, p. 109913, 2021.
12. Y. Chen and E. Patelli, "Towards robust prediction of material properties for nuclear reactor design under scarce data: A study in creep rupture property," in *Proc. Reliability Computations in Sustainable and Resilient Development*, Beijing, China, 2024, pp. 100–109.