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Physics-informed machine learning meets renewable energy systems: A review of advances, challenges, guidelines, and future outlooks

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HIGHLIGHTS

- Physics-informed machine learning for various renewable energy systems was summarized.
- Wind energy is in the spotlight of applying PIML among all renewable energy systems.
- PIML applications in solar, geothermal and biomass energy systems is in infant stage.
- Neural network is the most applied ML method in all of renewable studies.
- Indicator and criteria for selection PIML methods besides available Package and tools for implementing PIML was introduced.

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ABSTRACT

Physics-informed machine learning (PIML) has emerged as a powerful paradigm to combine machine learning techniques with physical laws to enhance the accuracy, reliability and interpretability of machine learning (ML) models. This review presents recent advances in the application of PIML in renewable energy systems (RESs) through different aspects from macro-scale to micro-scale including wind energy (farm modeling, blade analysis, power output, spatiotemporal analysis, fault detection), solar energy (flat-plate collectors, photovoltaic, parabolic trough, heat transfer coefficients), biomass energy (kinetic reaction, syngas composition, biofuel production), geothermal (energy extraction, heat-exchanger performance), ocean current, and hybrid RESs. Following a discussion on different integration approaches of ML models and physics, the review critically analyzes diverse PIML approaches and architectures adopted in RESs by highlighting the progress in well-established technologies such as wind energy and emerging areas like ocean energy where PIML applications are still in early development. Moreover, insights on how a wide range of algorithms and optimization strategies have been adopted to solve domain-specific challenges within RESs using PIML are provided. Furthermore, current tools and open-source packages that support PIML implementations are also reviewed. Additionally, it outshines key criteria, indicators and guidelines for novel strategies to implement PIML in RESs. Finally, current challenges and future prospects are outlined.

1. Introduction

1.1. Broader context

Transition from conventional fossil fuel resources to renewable energy technologies in the coming years is not a choice anymore, rather, it is considered as a mandatory option among the global policymakers. In this regard, the United Nations (UN) proposed several action plans including Millennium Development Goals (MDG) which planned for the period of 2000 to 2015 and Sustainable Development Goals (SDG) for 2015 to 2030, planning to address several important issues in front of our society [1–3]. Currently, the most important UN action plan is SDG which includes 17 Goals (with 169 targets) to solve crucial problems in front of our world with diverse views from education, inequality, poverty to global issues like energy, water and climate change. It was realized that the Goal 7, which focuses on “Clean and Affordable Energy for All”, has a relation with 143 targets of SDGs [4], making it the most important goal among others and highlights the vital role on realization of other SDGs by 2030. On the other side of the coin, the global energy sector (which heavily rely on fossil fuels) is responsible for significant

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portion of greenhouse gaseous (GHGs) emission throughout our blue planet which for decades continuously (except the global COVID-19 crisis situations [5]) increase GHGs with CO_2 at the forefront that reached to more than 32 million tons in 2020, mainly by the United States and China as the main player in generating CO_2 to the atmosphere [6]. The emission of these huge amount of GHGs throughout the environment have drastically changed the world with direct and indirect issues [7], however, the most important effect is the global warming which adversely threaten the environment and our societies through the increasing the sea levels [8], frequent extreme climate events [9,10], destroying wildlife and plants [11], just to name few. However, the renewable energy systems (RESs) seem as a promising alternative for the future energy mix, in which the combination of these sources with conventional resources contributed to a major systemic transformation in global energy policy implications. The well-established renewable energy sources are solar energy, wind energy, biomass energy, geothermal energy, hydropower energy, and ocean energy (tidal and salinity gradient energy) with solar and wind energy at the highest share of clean energy systems all over the globe. One of the main drawbacks of developing RESs in recent years was the high cost of energy production in comparison to utilizing conventional energy sources, however, in recent decades the production cost of solar cells and wind turbines dramatically decreased, making them more competitive with fossil fuel resources. Importantly, the development of RESs can be viewed from two different angles. The first is to increase efficiency through using high-performance materials. A good example is increasing the efficiency of solar cells upper than their limits through advanced materials [12,13]. The second one is to increase the efficiency of the RESs by optimizing their configuration/process through innumerable numerical methods. A prominent example is optimizing the layout of wind farms or optimal conditions during a process for biogas production. Among numerous tools in this context, some of the well-established strategies can be mentioned, such as computational fluid dynamics (CFD), nature-inspired metaheuristic approaches and machine learning (ML) methods. In the last two decades, ML methods as an advanced strategy, vastly adopted by scientific community in various disciplines, compared to previously numerical methods, because of its higher performance in different aspects like accuracy, computation time and lower cost of computation. In this regard, various machine learning approaches applied in different RESs.

1.2. Classic machine learning methods and applications

Data-driven methods, as the cornerstone of ML, have been employed for several decades in different fields of physical science and engineering to analyze the behavior of systems. However, it can be point out that Prof. Tom Mitchell was one of the first pioneer who presented a systematic overview by introducing the term of “Machine Learning” in several reviews, book chapter and research paper [14–17], although the term has sporadically been used in several papers in 70’s [18,19]. The ML field matured by introducing the concept of deep learning (DL) in 2006 by Noble Prize Winner; Prof. Geoffrey Hinton [20] and the field explored new realms in the whole spectrum of science. Indeed, ML has been employed in wide range of science and various subsets including biology [21–23], chemistry [24–26], materials science [27–30], energy storage [31], CO2 capture technologies [32], space science [33], agriculture [34–36], even economy [37,38] and social science [39,40]. Therefore, it is hard to elucidate the unprecedent impact of ML to our world, thus, this impact is just elucidated by a simple example. As anticipated by epidemiologists, the next pandemic which can lead to over 10 million deaths annually will be the emergence of drug-resistance pathogens [41]. But the problem is that developing new antibiotics to cope with new pathogens which have resistance to currently available antibiotics could take decades due to various clinical conditions while it also needs a lot of resources and investments without any guarantee to reach to the suitable results. However, recent studies showed the impressive power of advanced ML models in finding antibiotics for drug-resistance pathogens [42] and proposed several candidates against drug-resistance pathogens [43]. Fig. 1 shows different approaches of ML [44], however, it should point out that, to avoid repetition, here, the aim is not to explicitly discuss on detail features of each approach, where comprehensive discussions can be found in previous studies [45,46].

2. What is physics-informed machine learning (PIML)?

The first steps of physics-informed machine learning (PIML) was taken in the beginning of 2018 by introducing the concept of employing hidden physics models that are essentially data-efficient learning machines, capable of leveraging the underlying laws of physics, expressed by time dependent and nonlinear partial differential equations (PDEs) to extract patterns from high-dimensional data that generated from experiments [47,48]. Subsequently, the concept by presenting the physics-informed neural network (PINN) was outshine in 2019 [49]. In short, the PIML is a method that combines the conventional data-driven ML methods with physical law. Through this approach the energy, mass and momentum conservation physical laws as well as observational biases are embedded into ML methods, ascribe to the synergy provided by taking the advantage of data-based and physics-based approaches simultaneously. Using physics has several advantages for conventional fully data-driven ML method. i). It can guarantee that the prediction follows a rational path with less errors, because the prediction is based on fundamental physical principles. ii) The model can learn with limited number (i.e., sparse) of data, compare to fully data-driven methods because the fundamental physical law principles assisted the model. iii). The results of a developed model based on physical laws are often easier to understand and more interpretable to explain in comparison to the black-box nature of ML models. (iv). Last but not least, the developed model can generalize rather than fully data driven ML methods. These significant advantages of PIML, all together have synergies in accelerating scientific discoveries in various fields which bring the implementation of this approach more into the spotlight in the coming years.

It is important to note that, for evaluating the strength and robustness of PIML compare to classic ML, various error metrics were used as benchmark such as Mean Square Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Normalized Root Mean Square Error (nRMSE), Symmetric Mean Absolute Percentage Error (SMAPE), Mean Absolute Scaled Error (MASE), Root Mean Squared Logarithmic Error (RMSE_log) or other well-known metric like proportion of variance in the dependent variable (R^2). Moreover, sometimes two or three PIML methods were compared to determine the effectiveness of newly developed models over the well-known models, however, this approach has not been adopted too often.

A conceptual framework on PIML is illustrated in Fig. 2 which can be divided through four main applications (mainly for prognostic and health management [51]) by employing various types of knowledge such as empirical/physical models, physical laws, expert knowledge, statistical equations etc. just to name a few.

2.1. Application of PIML in different fields and disciplines

All said, the PIML swiftly becomes one of the hot keystones across different disciplines and various scientific fields. Several reviews on the application of PIML have been presented in the last couple of years. Kashinath and colleagues [52] highlighted the application of PIML in atmospheric science by presenting ten important case studies and illustrating its capacity in this context through downscaling, emulation, weather forecasting, climate processes, and drew a roadmap for employing PIML in atmospheric science. One of the main domains of PIML is to address the heat transfer problems [53] and fluid mechanics. Cai et al. [54] reviewed the application of physics-informed neural network (PINN) in fluid mechanics and brought three case studies namely i) three-dimensional incompressible flows ii) two-dimensional

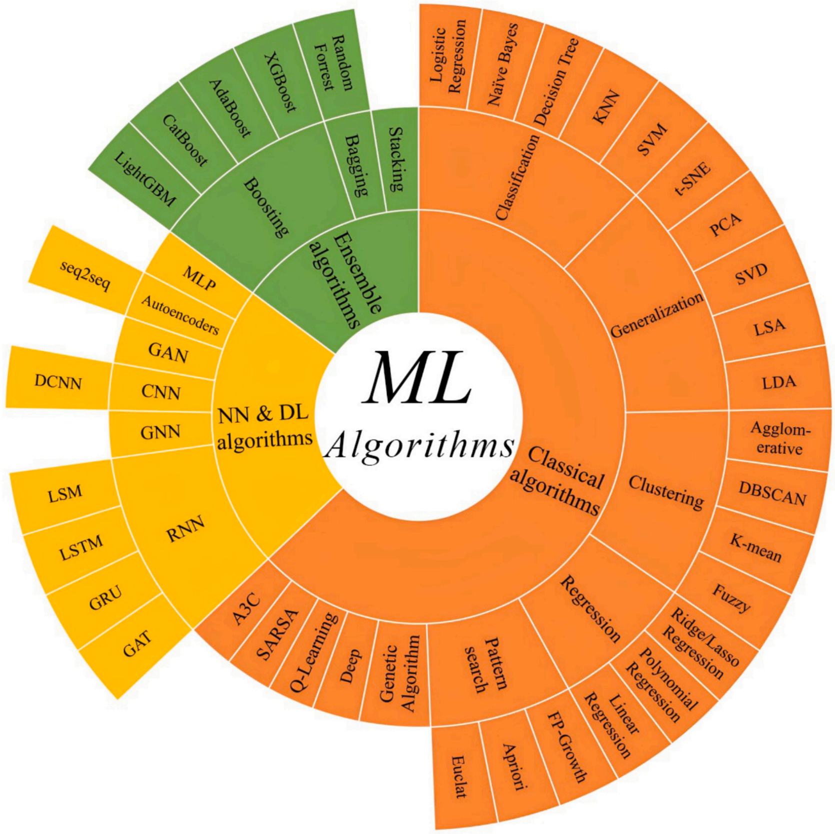

Fig. 1. Various algorithms of machine learning [44].

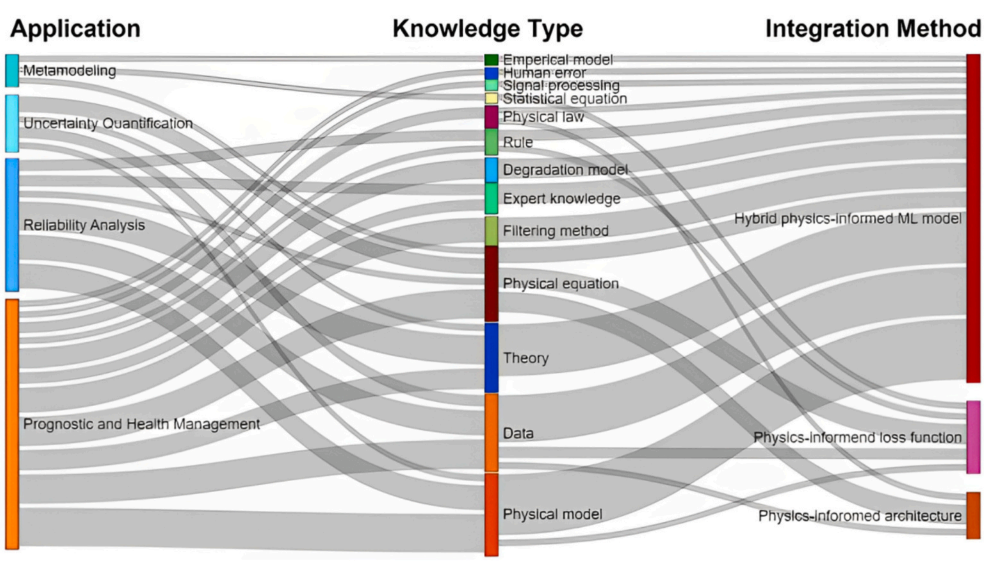

Fig. 2. Relations among application, knowledge type, and integration method of PIML [50]. Repreinted with permission from Elsevier.

compressible flows and iii) biomedical flows into the spotlight and emphasized on the new realm of PINN that could be addressed in the future for industrial applications where previously they could not be fully tackled by CFD approach. Huang and co-workers [55] discussed the necessity of implementing PINN in power systems because of limitations in front of conventional ML and deep learning such as requiring high-quality/quantity training data, inconsistency in solutions, and difficulty in interpreting results, etc. They showed that the main domains of PINN in power systems are in parameter estimation, dynamic analysis, calculating and optimizing power flow, and anomaly detection. Importantly, potential application of PIML in reliability and systems safety was outshined in detail by Xu et al. [50]. Rai and Sahu [56] discussed the potential application of PIML on cyber-physical systems as hybrid method for future advanced modeling in the field. Guo et al. [57] highlighted the application of physics-guided ML in electromagnetic data imaging through three implemented approaches i) learning after physics processing ii) learning with physics loss, and iii) learning with physics models. Moreover, application of PIML in materials science with a focus on life cycle assessment [58] and specific methods of preparation such as additive manufacturing, was also exhibited in previous studies too [59]. Rabee and co-workers [60] focused on the progress of physics-guided artificial intelligence approaches on designing complex compositional materials. They anticipated that physics-guided AI will increasingly contribute to the understanding and design of compositionally complex materials, driven by the rapid advancements in AI algorithms and resulting in more accessibility to high-quality materials datasets, and the availability of high-performance computing resources. Reddy et al. [61] discussed on potential of the PIML methods in civil engineering and emphasized on three aspects which are structural design and analysis, structural health monitoring, and building information modeling. It is worth noting that applying PINN in energy storage systems, particularly in Li-ion battery systems, was also extensively discussed [62,63]. Although classic machine learning was thoroughly applied in Li-ion batteries, the PIML in this context mainly assisted in thermal management, temperature distribution, fault detection, and electrochemical models [64,65].

Importantly, the PIML approach in renewable energy systems applied for specific purpose based on the type of system. For instance, in wind energy technology the focus is on wind farms and turbines with an emphasis on improving, optimizing, and estimating power output, wake field reconstruction, fault detection, and lifetime cycle assessment, just to name a few. In solar energy systems, predicting and increasing power efficiency and heat transfer coefficient of photovoltaic panels and solar thermal collectors (flat plate, evacuated tube etc.) through PIML are in the spotlight. Furthermore, for geothermal energy the PIML methods are utilized to evaluate the potential of energy extraction/recovery and predict the conditions of fluids and the temperature of reservoirs. For biomass energy, understanding and predicting complex chemical reactions and designing reactors through assisting the PIML approaches by considering important parameters such as scalability are frequently brought into the spotlight. For ocean current energy and hybrid renewable energy systems the current stage of employing PIML is just limited to a very few studies.

2.2. Objective of the present review

As reviewed above, PIML methods have been employed in several disciplines and fields, however, its potential on the RESs has not been realized yet. Therefore, the main objective of this review is to highlight recent advances of PIML applied in various types of RESs including wind energy, solar energy, biomass energy, geothermal energy, ocean current energy conversion, and hybrid RESs (Fig. 3). In this regard, the review is intended to open new windows in front of researchers who work in different types of RESs and provide possible avenues for the future of this fast-growing field of renewable energy schemes. It is important to note that, to avoid redundant and unnecessary information on the fundamental background behind PIML and their principles which are repeatedly presented in the literature, these principles have not been extensively discussed again, and the readers are referred to previous studies accordingly. The structure of the review is as follows. In the first step the integration modes of PIML were briefly discussed and it followed by the current available tools and packages for applying, implementing and assisting PIML procedures. Afterwards, the application PIML in all RESs has been thoroughly reviewed and. At the end of this review, the current status, challenges and future prospects of PIML in RESs are highlighted.

2.3. Data collection strategy and review questions

To write a systematic review analysis, it is crucial to follow a logical path and specific methodology based on scientific cornerstones for collecting data such as using Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) -updated version 2020- [66] which highlighted the general principles and criteria in this context. In this

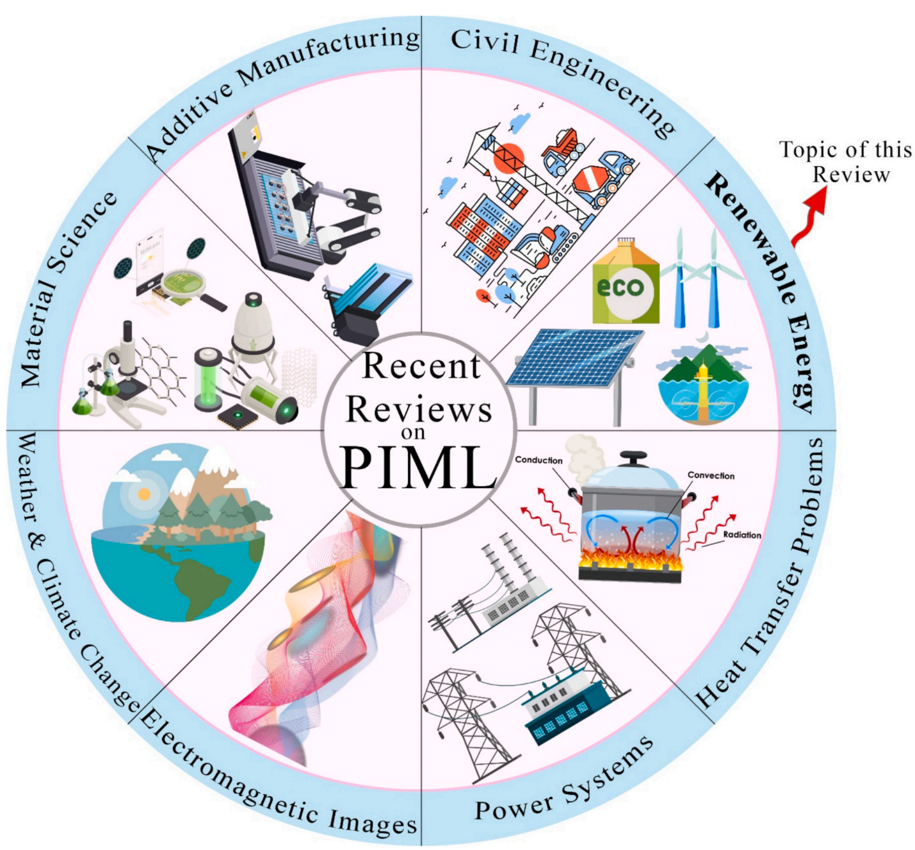

Fig. 3. Application of PIML that currently reviewed on different fields.

regard, search strategies were applied based on several criteria which can be categorized as keywords including physics-guided machine learning, physics-informed neural network, physics-guided neural network, physics-informed (and physics-guided) deep learning, PIML, PINN in combination of all renewable energy systems keywords including solar energy, solar collector, photovoltaic (PV), wind energy, turbine blade, wind turbine, geothermal energy, biomass energy, ocean current energy, wave energy, and hybrid renewable energy and all of their components. It is important to note that Google Scholar and Web of Science (WoS) were used as databases of data collection. The most important criteria for selecting a study were (i) whether these terms were used in the title, abstract, or keywords, and (ii) whether the study explicitly and directly applied one of the PIML approaches to one of the RESs or its components, which was evaluated by reading the abstract. Moreover, as the concept of PIML was first introduced in 2019, a filter based on the year of publication was applied to show the results starting from 2019.

Importantly, the review tries to answer several important questions from a broader context to very specific concepts including:

(i) What is the state-of-the-art progress on implementing PIML across all RESs from its beginning development in 2019?
(ii) What are the advantages of applying PIML in RESs compared to classical machine learning approaches?
(iii) What aspects of RESs were brought into the spotlight by the PIML and what aspects were not examined?
(iv) Elucidating the types of PIML applied on various RES and the possible pros and cons in that specific study (if available).
(v) Highlighting the novel strategies (architecture) rather than the conventional PIML method that is employed in this context.
(vi) Examining what PIML methods on what problems (i.e, blade fault detection, spatiotemporal analysis, reactor design, solar collector's efficiency etc.) have been applied?
(vii) What are (if available) the most well-established and efficient approaches (or architectures) for solving specific types of problems?
(viii) What are the current challenges, limitations and future prospects on implementing PIML methods across all aspects of RESs?

3. Integration modes of PIML

In order to construct a learning algorithm, physics-informed models involve embedding appropriate observational, inductive, or learning biases that guide the training process for discovering solutions consistent with physical laws. PIML integrates domain knowledge into model development by incorporating physical laws and constraints into the learning process. These methods are broadly categorized based on how such biases are introduced.

3.1. Physics-informed based observation biases

When a ML model is trained on observational biases, it learns functions, vector fields/operators that innately capture the physical structure that are presented in the observations. This approach ensures that the model's understanding of the system is grounded in empirical or physically meaningful representations which can act as a data-driven foundation for physics-informed learning. Importantly, observational data plays a focal role to the success of modern ML and could be considered as the simplest way to introduce bias in this context. Indeed, with enough data that could cover the input space, ML models can interpolate accurately, even in high-dimensional environments. In physical systems, recent advances in sensors make it possible to collect diverse observations across time and space. These data inherently reflect physical laws that resulted in their generation; they principally can serve as a weak means of embedding such principles into ML models during training. In a nutshell, observational biases are introduced by training data that innately encode the underlying physics or via well-designed data augmentation strategies that reflect physical principles. Some examples with this approach can be found in the literature [67–69].

3.2. Physics-informed architecture through inductive biases

This approach is another branch of specialized neural network architecture that intrinsically incorporates prior knowledge and inductive biases related to specific prediction task. Inductive biases refer to initial assumptions that can be embedded into a machine learning model's architecture through specific interventions to ensure that the model predictions innately comply with a set of physical laws that are formulated as mathematical constraints. This is often considered the most rigorous approach to make a physics-informed learning algorithm since it enforces strict adherence to the underlying physical principles. However, it should be noted that this approach is generally useful for dealing with relatively simple symmetry groups (like translations, permutations, reflections, and rotations) that must be known in advance, and they can result in complex, hard-to-scale implementations. More importantly, the architectures can be effectively applied to solve differential equations using NNs in the whole spectrum of renewable energy systems that explicitly need to meet required initial conditions (fixed boundary, gradient/flux boundary, boundaries between two medium, or a combination of them) such as Neumann boundary conditions [70,71], Dirichlet boundary conditions [72,73], periodic boundary conditions [74,75], interface conditions [76] and Robin boundary conditions [76] for wide range of crucial parameters in renewable energy systems modeling, including temperature, pressure, velocity, heat and mass flux, just to name a few.

3.3. Physics-informed loss function

Learning biases can be incorporated through the careful selection of loss functions, constraints, and inference methods that guide the training process of a machine learning model to explicitly promote solutions aligned with physical principles. Although these soft penalty constraints only enforce the physical laws approximately, they offer a highly adaptable framework for embedding a wide range of physics-based biases including integral, differential, or even fractional equations. These diverse strategies for steering a learning algorithm toward physically consistent outcomes are not mutually exclusive and can be effectively integrated to develop a wide spectrum of hybrid physics-informed learning systems. In another words, this involves adding soft constraints penalty terms that encourage the model to not only fit the data but also follow known physical laws like conservation of mass or momentum. It can be defined as a form of multi-task learning whereas the model learns from both data and physics. A prominent example of employing this approach is physics informed neural network (PINN) and their derivatives [77–79]. This approach, due to its flexibility, was widely adopted in constructing PIML models for renewable energy systems.

3.4. Physics-informed hybrid model

Apart from all the above-mentioned approaches in PIML, it is clear that each method has its pros and cons, thus, integrating them could be beneficial to take advantage of them concurrently. Indeed, these different approaches for biasing a learning algorithm toward physically consistent solutions are not mutually exclusive and can be effectively combined to yield a very broad class of hybrid approaches for constructing superior PIML models [80]. Indeed, the combination of biases makes the hybrid models much versatile and powerful toward real-time prediction of complex applications such as electro-convection and hypersonic. It should be noted that many problems in the renewable energy systems are formulated based on this approach because of its superior flexibility.

4. Tools, packages and frameworks in PIML

To support researchers in implementing PIML techniques, several libraries, tools, and software packages have been developed. These tools are particularly valuable for newcomers to the field, as they simplify the integration of physics-based constraints into machine learning models. It should be noted that there are probably more packages and tools in this context, herein, several of the prominent approaches are just introduced accordingly. Below, we provide an overview of widely used tools and their relevance to the studies discussed in this review.

4.1. DeepXDE

DeepXDE is an open-source library designed for solving differential equations and scientific machine learning tasks [81]. It supports PINNs and provides flexibility in handling both strong and weak-form integration of governing equations. Its user-friendly interface supports a wide variety of differential equations and integrates well with TensorFlow. However, one of the main limitations of DeepXDE could be the customization for highly complex physics problems.

4.2. SciANN

SciANN is a lightweight library specifically built for scientific computing and machine learning based on Keras/TensorFlow [82]. It focuses on simplifying the implementation of PINNs and hybrid models. It could be applicable to problems requiring numerical solutions to partial differential equations, such as fluid dynamics in ocean energy systems but it is not a powerful framework for complex PIML problems.

4.3. PINN frameworks in Julia (NeuralPDE.jl)

Julia, known for its high-performance numerical computing, offers the packages NeuralPDE. The NeuralPDE.jl framework is a solver package which consists of neural network solvers for partial differential equations using PINNs and the ability to generate neural networks which both approximate physical laws and real data concurrently. This framework has numerous features and advantages. For instance, it is capable to generated extended loss functions for parameter estimation and operator discovery. Moreover, the framework has the ability for the automated construction of Physics-Informed loss functions from a high-level symbolic interface. The NeuralPDE delivered acceptable performance on addressing complex problems in multiphysics such as the Doyle-Fuller-Newman (DFN) Model and demonstrated how the PDEs can be formulated and solved by NeuralPDE [83].

5. Applications of PIML in renewable energy (Where we stand?)

5.1. Wind energy systems

The application of PIML is mostly applied in wind energy because of technological maturity and large number of data and previous practices. However, one thing that should be mentioned is that some sections here have overlapped with each other and may be considered as sub-categories of others, however, based on the title and the focus of studies they are categorized in this way.

5.1.1. Farm modeling

Application of PIML in wind energy is quite wide, but farm modeling, due to its vital role in large-scale implementation of renewable energy is of great importance. Understanding the dynamic wake of wind farms is at the focal point of many PIML studies due to its crucial role in optimizing the layout and extracting power output [84]. Zhang and co-workers [85] developed a PINN with spars data through light detection and ranging (LiDAR) measurements to capture the wake dynamics of a wind farm under various scenarios, particularly in yawed conditions. Each PINN integrated the N-S equations (physical constraints) to loss functions (both data-loss and physical-loss) to improve the model's accuracy and reliability. Moreover, the model developed by conducting Large Eddy Simulations (LES) to produce high-fidelity datasets of the wake field within the wind farm for reconstructing wake fields and was trained for both conditions, aligned -non-yaw- (ideal conditions) and misaligned (yawed) turbine conditions. The results indicated that the PINN model at different time-steps ($t = 40$ s as the reference) delivered acceptable accuracy and demonstrated a high degree of concordance with LES outcomes, of great importance in trajectory capture. Similar studies with the focus dynamic wake reconstruction under yawed conditions through assisting PIML reported accurate and reliable performance compared to pure data driven and numerical methods [86].

To reach the maximum exploitation of wind by finding the optimum layout of the wind farm, Wu et al. [87] in a comparative study through physics-guided approaches compared three different meshes including staggered, unstructured, and sunflower (Fig. 4a). The model implemented the Jensen wake model as physical knowledge while optimizing by genetic algorithm (GA) to find the optimal conditions in different scenarios. The findings showed that although, under variable wind directions all approaches showed similar performance, when the unidirectional of wind assumed to be uniform, the highest output achieved by staggered mesh, while the sunflower mesh exhibited good performance under all conditions. However, it should be noted that, although the study used physical knowledge it could not be considered as PIML, but the study can be further extended to PIML to examine different meshes in this context.

In a recent study, Song and co-workers [88] suggested to improve precision and reduce the computational time of conventional PINN by integrating the PINN with a cosine annealing algorithm (CAA) and dynamic weight strategy (DWS) solely and in an integrated strategy for predicting dynamic wake fields. The PINN was developed by integrating 2D Navier-Stokes (NS) equations with the residuals of LiDAR data, and the actuator disk model into the loss function and the model's performance under four scenarios of PINN, PINN-CAA, PINN-DWS and PINN-CAA/DWS was examined. The findings demonstrated that the MRMSE of the LiDAR center wind speed prediction was reduced by 27.1 %, 9.4 %, and 40.5 % for the PINN-CAA, PINN-DWS, and PINN-CAA/DWS correspondingly. Moreover, the study by employing step-by-step strategy used the advantage of transfer learning in model to improve the computational speed more than 56 %. It is worth noting that implementing novel algorithms in the learning process and introducing physical knowledge strategy in a well-established PINN substantially improved the accuracy and consistency.

Cobelli et al. [89] developed a PIML and modeled the wind field by focusing on reconstructing the inflow velocity field around wind turbines by integrating LiDAR measurements and 2D NS PDEs within neural network. The performance of the model was improved by assisting different configurations of PINN such as cyclic learning rates, adaptive activation functions, and self-adapting weights to improve model performance and the results were compared with conventional CFD. The findings showed that the PINN approach has superiority in terms of accuracy, efficiency and runtime compared to traditional numerical methods even though the sparse LiDAR data were presented as input. Wang et al. [90] integrated PINN with sparse LiDAR data and Navier-Stokes equations as the constrains for predicting and reconstructing the wake dynamics of wind farm (Fig. 4e). The accuracies of the model were examined by using different arrays of LiDAR data and it was realized that the model can significantly reduce the energy losses related to wake effects, even with limited data as well as under variable operating conditions. It is important to point out that the two recent studies discussed above show how PINN by employing sparse LiDAR data outperformed conventional ML and CFD methods.

Schröder et al. [91] employed a transfer learning approach and integrated a data-driven method with physics for anomaly detection in

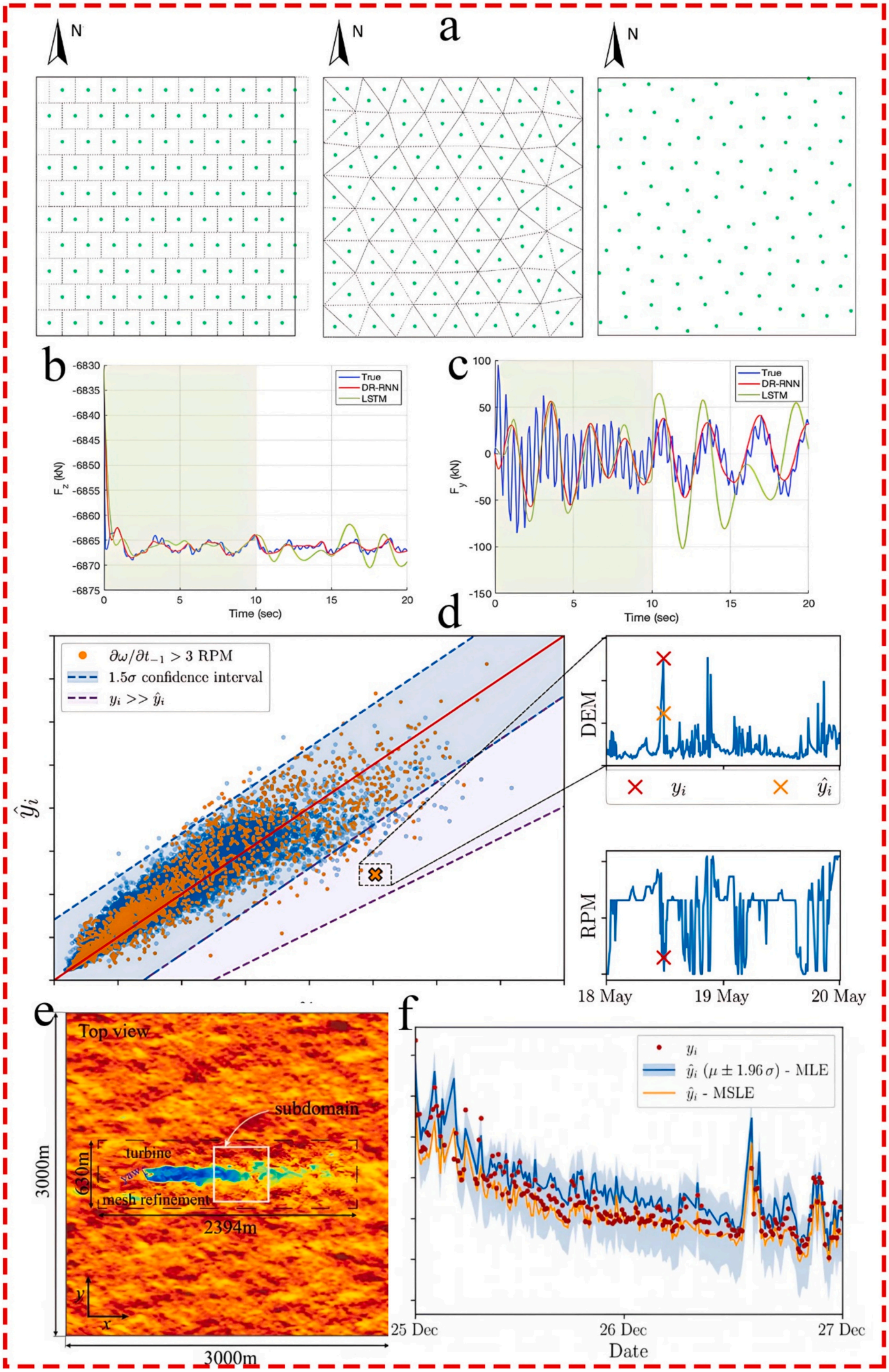

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Fig. 4. a) Potential turbine positions (green points) defined using different approaches from left to right staggered mesh, unstructured mesh and sunflower mesh [87] Reprinted with permission from Elsevier. Comparison of response predictions between DR-RNN and LSTM models for forces and moments at the tower base section: b) force along y-axis, c) force along z-axis [96] Reprinted with permission from Elsevier. d) DEM predictions (*yi*) versus measurements (*yi*). Red line indicates identity (*yi* = *yi*). Region of significant underestimation (*yi* >> *yi*) shown in purple. Time instances of sharp yaw angle transients ($\partial\theta/\partial ti{-}1 > 10^{\circ}$) highlighted in orange. (right) Ten-minute time series window of lateral bending moment at LAT016 (*Mtl*) strain values (in N·m). Areas of rapid and severe variation in the lateral bending moment ($\bigtriangledown Mtl >> 0$) are marked in red. Yaw angle (θ) shown in light blue [97] Reprinted from open sources. e) The geometry of the computational domain and mesh-refined area, with the subdomain space marked for dynamic wake reconstruction [90] Reprinted with permission from Elsevier. f) Time series (*yi* or **DEMreal**, shown in red) and estimated values (*yi* or **DEM pred**, shown in blue) along with 95 % confidence bounds (1.96 σ, where σ is the standard deviation) of the relative error for OWT1 FA obtained via MLE. Estimates from MSLE (*yi* in orange) are also displayed [97]. Reprinted from open sources. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

wind farm through two methods which are PINN trained by large supervisory control and data acquisition (SCADA) and stacked denoising auto-encoder that used subspace transfer learning. The results showed that the integration of recalibrated SCADA data decreased the errors of prediction and the standard deviation by around 1.64 % and 15 % respectively. Of particular interest, the model showed an exceptional improvement in fault detection where the precision increased from 50 % to 100 %.

Hassanpoor et al. [92] constructed a PIML for optimizing wind farm layout and flow field through by incorporating the Navier-Stokes equation with a hierarchical encoder-decoder convolutional neural network (CNN) by training the model via generated CFD data incorporated to physics-based loss function. In order to maintain the uniform consistency of learning throughout the field, the logarithmic transformation to the loss function was utilized. The model precisely predicted the flow field with an acceptable R^2 around 0.955 for both streamwise and spanwise flows while comparison of the annual energy generated by the PIML model with validated CFD data a marginal error around 1.25 % was calculated, highlighting the strength of the proposed model. Interestingly, the study applied a variable weighting approach for the loss function that effectively extracted the loss of each component based on their contribution. Indeed, this strategy was in contrast of previous approaches that designated the same loss weight to all components equally reducing the accuracy of the model as it showed in this study that the RMSE for flow prediction for variable weighting compared to fix weighting decrease nearly 33 % (from 0.18 to 0.12 m/s).

Ye et al. [93] proposed a precise model to predict the wind field advection and diffusion through a physics-guide ML method named AIRU-WRF integrated the kernel functions with exogenous predictors and linked numerical weather predictions biases to driving mesoscale weather conditions for offshore wind turbines in US Atlantic. The PIML model was assisted with direct numerical weather predictions -NWP- (at specific center in Rutgers University), which were forecasted for both the historical observations, as well as future forecast horizons and incorporated by two spatio-temporal functions. It was concluded that the developed model outperformed than all methods, particularly, improved the accuracy of mean absolute errors compared to NWP, GOP, ARIMAX and Long Short-Term Memory (LSTM) by up to 22.5 %, 21.4 %, 27.1 % and 29.1 % respectively. It is worth noting that this study highlighted the significance of reliable numerical data used in the model for developing a robust PIML.

Tian et al. [94] assisted a residual-connection with a NN to leverage Navier-Stokes equation and developed a physics-guided ML model (RC-PINN) to reduce the gradient vanishing issue for reconstructing wind field to cope with the issue of noisy data capability in conventional PINN models. Importantly, the NS equations, which are unified by LiDAR measurements, were encoded into the RC-PINN to reconstruct the spatio-temporal wind speed and direction leading to a hybrid integration mode. It was shown that the method can effectively cope with superior performance compared conventional PINN in terms of accuracy, rapid convergence, and even when actual LiDAR noisy data is applied.

Muscari et al. [95] constructed a physics-informed ML model based on an unsupervised approach of dynamic mode decomposition (DMD) assisted by LES data to model the wake and to optimize the Pulse and Helix dynamic mechanisms toward improving power production and wake mixing efficiency considering a 10 MW DTU wind turbine as the referenced turbine. The authors adopted two scenarios for evaluating the wake and it was realized that counterclockwise helix obtained the fastest wake recovery, up to 80 % flow recovery of the free-stream velocity, while the clockwise struggled with presenting different wake features and turbulence levels.

Li and Zhang [96] presented a physics-guided residual recurrent neural network (DR-RNN) model for monitoring structure health and maintenance of wind farm by predicting the response of wind turbines. The PIML model was trained with actual numerical data to update the training parameters and calculate loss function where it delivered exceptional performance by reducing training error and test error to 0.023 and 0.031 respectively, while it predicted responses accurately even with a large time step of 10^{-2}. The DR-RNN performance, in comparison with LSTM outperformed, in various scenarios particularly in long-term estimations. Indeed, the comparison of models showed that the DR-RNN captured the structural response within x-axis and z-axis compared to LSTM (Fig. 4b, c). However, the model also suffered from high-frequency oscillation because of linearized state-space equations.

5.1.2. Fault detection

Yucesan et al. [98] to reach an appropriate schedule for maintenance and to reduce operational cost, implemented an integrated physics-informed ML method by combining physics-based and data-driven factors by combining reduce-order physics model bearing fatigue damage and NN to interpret the grease degradation toward finding the grease quality and lifetime during the operation of turbine. Importantly, the authors employed mean-absolute error (MAE) instead of MSE as the loss function to train the hybrid model using the grease samples collected from 100 turbines over 6 months. Indeed, the reason for using MAE over MSE was that although the MSE favors convergence toward the data mean, it performs poorly with skewed distributions unlike the MAE which targets the median (50 %). Moreover, the model exhibited precise prediction in bearing fatigue lifetime for varied grease quality conditions and optimized the interval for recharging the grease.

Khan et al. [99] constructed a PIML by employing Bayesian neural network combined with 40 sensor features as an input layer follow by three fully connected layers with rectified linear unit (ReLU) activation to extract the feature for wind turbines sensor's fault detection. The PIML was implemented in TensorFlow framework and (Adaptive Moment Estimation) Adam optimizer with an initial learning rate of 0.0001. Importantly, the model was compared with ten conventional classifier ML models including random forest (RF), support vector machine (SVM), neural network (NN), CNN, LSTM+CNN and compared them through accuracy, precision and recall, outperformed than other models. It is interesting to note that, although the proposed model did not achieve the best leads to training time and inference speed, the PIML model resulted in an optimal balance between these two parameters.

Fabian et al. [100] developed a physics-guided deep learning method based on cyclic spectral coherence (CSC) and real-world data for early fault detection turbines gearboxes through an automate monitoring approach. They used an unsupervised deep learning method and utilized an autoencoder to interpret CSC maps derived from vibration signals, where it was well-trained with fine data from a normal turbine to recognize deviations signs of faults. Importantly, the autoencoder was utilized by five years of data from five healthy turbine (≈ 3600 CSC, 80 % training:20 % validation) and trained by 1000 epoch using mini-batch gradient descent (batch size = 16, randomly sampled) while the Adam optimizer (learning rate = 0.0005) was employed for efficient weight updates and convergence. Interestingly, the model had the advantage that by learning the normal behavior of the turbine in specific parameters it can predict the behavior of other turbines and facilitate fleet-wide monitoring. Indeed, PIML showed significant strength on evaluating bearing fatigue damage particularly with a focus on grease degradation in wind turbine systems [101].

Interestingly, recent studies proposed novel methods to employ new paradigms such as integrating digital twin approach in PIML for real-time failure of wind turbines [102]. For instance, Yucesan et al. [103] proposed a hybrid model based on a digital twin to integrate a physics-based reduced-order approach and data-driven kernels for modeling bearing fatigue while the model was also assisted by the uncertainty quantification using tailor-network layers and loss function to evaluate the bearing fatigue through grease degradation. To evaluate the strength of the proposed model, it was tested under different uncertainty scenarios, and it was reported that at the worst-case scenario the model may miscalculate the bearing fatigue only 4.7 weeks, which still outperforms pure LSTM. The findings illustrated that through a time history; the LSTM models compare to physics-based model for a single turbine within the training set, performed poorly, while the physical-based ML model accurately validated with observed data (Fig. 5b). Following that, in another study [104], the above-mentioned PIML model was further expanded for probabilistic two-step method to examine the uncertainty in grease parameters caused by the variation in quality by combining RNN with bearing fatigue and grease damage models to estimate the bearing fatigue. The MAE used as loss function instead of MSE based on the above-mentioned reason. The PIML model delivered 90 % accuracy in prediction of remained-useful lifespan of bearing with only 7.8 weeks error in worst case scenario. It is important to note that the above discussed studies indicated that combining RNN with SCADA data is appropriate for understanding complex dynamic system parameters by PIML, because RNNs are well-suited for modeling time-series and dynamic systems, as they extend feedforward networks by incorporating temporal dependencies through recursive state updates.

Lee and colleagues [105] combined adaptive elite-particle swarm optimization (AEPSO) with Extreme Gradient Boosting (AEPSO-XGBoost) on an uneven SCADA dataset as a classifier integrated with physics-based CNN toward classifying faults and detecting various anomalies in wind turbines both of which trained with temperature of backed-bearing data. Through direct incorporation of physical constrains into loss function (physical loss and cross-entropy loss) the model was capable to capture the pattern and underlying relationships of data. The model was compared with several well-established model in terms of fault detection in different metrices of MAE, MSE, RMSE, R^2 and outperformed all. These results were obtained through improved wind turbine fault classification and prediction by optimizing XGBoost and combining resampled SCADA data with physics-based CNN features. In other words, the AEPSO-XGBoost and PDCNN models work synergistically, that while XGBoost could detect known faults precisely the physics-based CNN captures unexpected anomalies to boost system resilience.

Alotibi et al. [106] developed a PIML method by integrating an unsupervised algorithm of Isolated Forest within physics-informed approach to construct a model for fault detection and cyber-attacks to control systems of wind turbines. The physics-based component validates power signals against physical laws, while Isolated Forest detects anomalies by analyzing the enriched feature space that includes physics-based indicators. Performance of ML algorithm with and without physic-assisted approach was examined and it was realized that the attack detection for physics-informed Isolated Forest is between 73 % and 97 %, with a false alarm rate of 18 % while for the standalone Isolated Forest a detection rate of 18-20 % and a false alarm rate of 19 % were obtained.

In an interesting study Shao and co-workers [107] developed a physics-based neural network for failure prediction of adhesive layer in carbon fiber reinforced polymer (CFRP) bonding joints in offshore wind turbine blades under diverse environmental stresses. The PIML model was developed based on the cyclic cohesive zone model, which was embedded by the multi-environmental stresses that integrated into neural network. The model's robustness in predicting the failure and lifecycle of CFRP was compared with finite element method (FEM), where the results showed that the RSME for the FEM model lies withing range of 10-20 %, in contrast to PIML, which mostly remained within 10 % or lower. Interestingly, the Sobol sensitivity was combined with PIML and results in to extract and ranking the most influential and vital parameters on the lifetime of the CFRP. It is important to point out that applying sensitivity analysis in PIML could be considered as a novel step in weighting the important factor contributions on the parameter that evaluated by PIML.

Liu et al. [108] in a novel approach proposed to integrate SVD for identifying model parameters with RNN and construct a physics-informed deep learning model for monitoring real-time adaptive modal parameters of an offshore wind turbines (Fig. 5a). In contrast to traditional PINN which mainly build based partial differential equations, the RNN was directly constructed based on 2D non-linear differential equations for solving the SVD problem which leads to lower the computing time by around six folds compared to standalone SVD while reduced the computation complexity and improving accuracy respectively. Indeed, integration of RNN-SVD resulted in overcoming the significant challenges of the random input initialization and time-increment factor for the network, which have been successfully addressed by the pattern matching strategy and adaptive step optimization, concurrently.

5.1.3. Lifetime assessment

Interestingly, Santos et al. [109] took the Minkowski logarithmic error (MLE) as a loss function to construct PINN for prediction fatigue and damage-equivalent moment (DEM) of turbine components. The model is implemented by data of strain gauges, SCADA (10 min intervals), and wave and tidal and wave data from maritime database. The results were compared for MLSE and PINN, where it showed exceptional accuracy which achieved R^2 values of 0.92 (fore-aft) and 0.99 (side-to-side) for offshore wind turbine, with long-term DEM errors (δLT) of 1.19 % and 0.59 % compared to 6.72 % and 11.9 % (for MLSE), respectively. The authors declared that the model is an alternative and more reliable tool for long-term fatigue prediction ascribes to conservative over-prediction which is crucial for offshore structures.

Following the above, in another study [97] a thorough analysis on integrating NN to 270 days real-world SCADA data, acceleration measurement, and maximum likelihood estimation (MLE) as loss function to develop a physics-informed ML model toward estimating the long-term fatigue load on an offshore wind turbine was performed. Interestingly, all measurements lied within the 95 % confidence interval (Fig. 4f), however, the predicted values tended to exceed the observed measurements on average due to the use of the logarithmic function in the MLE as it promotes over-prediction, introducing the desired conservatism to the model.

To better analyze the model's behavior under high load the predictions ($\hat{y}_i$) were plotted against measurements (y_i). As can be seen, the model's performance under high load conditions was well predicted and closely matched with measurements, with most points falling within the 1.5σ confidence interval and aligning with the identity line, however, minor over-prediction occurred at low loads (Fig. 4d-left side). However, the model failed to capture a sharp spike in DEM with substantial underestimating the structural response (Fig. 4d-right/top side). Interestingly, by further tracing this under-prediction it was realized that there was a severe and sudden variation on the RPM which caused a sudden spike in DEM (Fig. 4d-right/bottom side).

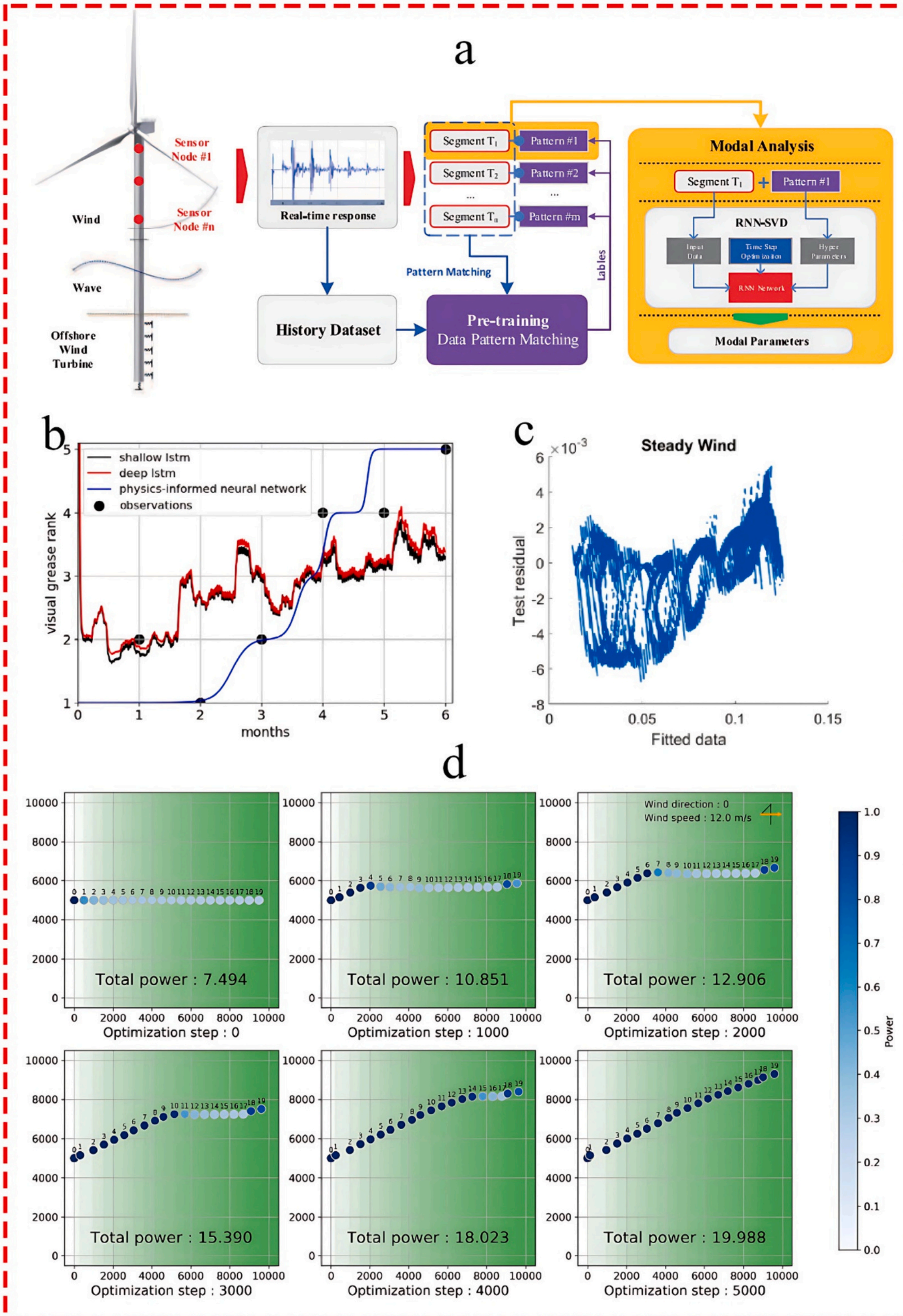

Fig. 5. a) Schematic illustration of the proposed physics-informed framework [108] Reprinted with permission from Elsevier. b) Prediction from recurrent neural networks versus observed rank for one of the turbines in the training set [103] Reprinted with permission from Elsevier. c) Fitted graph for steady state of angle of attack based on the developed PIML [116] Reprinted from open source. d) The results of layout optimization that displayed the layout evolution for different optimization steps. x, y axes indicate the grid of wind farm. The blue ball denotes the optimized turbine positions. The colors of the balls indicate power generations of turbines [110] Reprinted with permission from Elsevier. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5.1.4. Power output

Park et al. [110] combined wake-deficit model with graph neural network (GNN) as an advanced PIML to estimate the output power of wind turbines in various scenarios (up to 100 turbines, at size up to 4 km × 4 km, the flow direction 0-350°, wind speed up to 0-12 m/s). The model represents wind farm configurations as graphs, where nodes represent turbines and edges capture wake interactions. For examining the robustness of the model, twenty wind turbines were placed in a single line (as the worst possible power generation scenario) and the wind speed and direction were set as 0 and 12.0 m/s (Fig. 5d). The results highlighted the exceptional performance of the model, where, at the initial layout, the simulated power generation was 7.494, while it converged around 5000 steps with a power generation of 19.988 (Fig. 5d). It is important to note that, the GNN regarding its architecture has the advantage of generalizing across layouts for wind farm modeling.

As discussed above, in numerous studies different types of data have been utilized through hybrid integrated mode to construct PIML, among them, the CFD simulations have been extensively applied in renewable energy systems [111].

In this regard, Rezaei et al. [112] developed a PIML by incorporating the extreme gradient boosting (XGBoost) algorithm with generated data of CFD simulations of seven cases from two offshore wind farm in Sweden and Denmark to leverage physics-informed features such as turbine-level geometric inputs for power output prediction. They used three physical models to construct the PIML which are i) simple model based on turbine geometric, ii) using the modified wake model (Park's model) iii) and newly developed model based self-similar Gaussian model. The results demonstrated that the PIML for all three physic-based models outperformed than their originals with Park's model marginally delivered less errors among three PIMLs. Moreover, the strength of the PIML models showed acceptable predictions for random wind turbine cases with accurate power estimation through generalizability of the PIML due to introduction of physical interpretable features.

In order to facilitate the model validation over physical principles and modifications in non-stationary environments, Letzgus et al. [113] proposed an interpretable AI method for power output prediction using kinetic power of wind in classic mechanic on governing equation employing the air density and turbulence intensity correction as physical knowledge combined different ML approaches including ANN and RF. The proposed framework exhibited that the models incorporating physical factors perform better out-of-distribution scenarios since it systematically analyzed the factors which impact learned strategies. Of particular interest, models with higher alignment to physical strategies showed significantly better results. The framework also revealed that ANN models with enhanced regularization can reach high physical alignment.

Lei et al. [114] proposed an architecture-integrated PIML by combining stacked extreme learning machine (SXLM) as the ML method, embedded in an optimal power flow model as physical knowledge. The PIML model was decomposed into three phases of correcting, learning bias, and enhancing feature extraction. Moreover, it included a sample pre-classification strategy based on active constraint identification to simplify the learning task while utilizing reinforcement mode in the hidden layers to improve learning capacity. The obtained results indicated that the SXLM significantly improved both the accuracy and computation speed with high precision in predicting voltage magnitudes, power flows, and power outputs.

Gijon et al. [115] developed a PINN with hybrid integration mode by incorporating evidential uncertainty quantification to predict power output, as the function of pitch angle, wind velocity, and rotor angular velocity with physical constraints from the governing equations of wind turbines. An empirical model based on a classic model kinetic energy of incoming wind established and combined with real data from four wind turbines from La Haute Borne wind farm in France as physical knowledge of PIML. The evidential layer constantly estimated uncertainty, was closely aligned with absolute errors and enabled the definition of confidence intervals for the power curve, while it performed well across a diverse range of wind speed regimes and tolerated against noisy data. Indeed, the pure differentiable nature of the developed model makes it an ideal approach for building optimal pitch angle controllers.

5.1.5. Blade analysis

Baisthakur et al. [116] addressed the high computation time of the Blade Element Momentum (BEM) theory by developing a surrogate model based on PINN and replaced it with the conventional model in a comparative study for estimating aerodynamic load on wind turbine blades. The PINN model was assisted by the knowledge of numerically generated data from standard IEA 15 MW wind turbine and employed high-dimensional regression, refined by Adam optimizer, and replaced with the root-finding process in the BEM model. The surrogate PINN model speeded nearly the computation 40 times than root-finding method in solving BEM equations as well as achieved a 35 % reduction in computation time while it was examined the model performed well in both conditions of steady state (Fig. 5c) and turbulent flow. However, one of the limitations of the model was that the model focused on physical measurable factors, and it did not explicitly consider the wind shear and Reynolds Number effect on the angle of attack.

An active physics-guided blade pitch control method to increase the energy efficiency of vertically-axis wind turbine was proposed by Wisner and Yu [117]. The Spalart–Allmaras model with unsteady Reynolds-averaged Navier–Stokes equations and ANSYS FUENT was employed across varied wind velocity (3.5 7 and 14 m/s) with five different tip speed ratios (1.5, 2, 2.25, 2.5, and 3 m/s) for each speed to maintain efficient angles of attack (AA) of blades constant. It was found that through constant AA the time-average total power coefficient (TPC) increased 27.4-704 % for different scenarios with wind speed and TPC at 7 m/s and 0.481 was observed as the optimum conditions, correspondingly.

In an innovative contribution, Sun and colleagues [118] proposed a novel method for early failure detection of wind turbine blades by embedding the physics of acoustic energy conservation directly into to NN loss function. Interestingly, the model was trained by sounds data, generated in a laboratory wind turbine through a Bluetooth speaker installed within cavity of blade to generate controlled acoustic excitation, whereas an outer microphone captured the damage-related signals, which carried out preprocessing using Cross-spectral matrix analysis to augment the quality of signal. The model aimed to predict the failure associated to voids, adhesive joint failure, cracks in blades, compared with MLP and CNN. The results exhibited that the model outperformed, in which by using only 5 % of the training data it achieved an R^2 of 0.91 and an error index below 0.5 %.

5.1.6. Spatiotemporal modeling

Zhang et al. [119] integrated the Navier-Stokes equations with actuator turbine modeling, that assisted by LiDAR measurements as physical knowledge and combined neural network to construct the first digital twin PIML model for whole wind farm (offshore/onshore) in-situ spatiotemporal modeling. The results of rotor-effective speed along the centerline and the speed profiles exhibited the robustness of the model by accurate prediction in comparison to the true data (Fig. 6c). Importantly, when the model applied to predict for a new location, the digital twin implicitly accounts for correlations with neighboring LiDAR measurements based on the Navier–Stokes equations as well as data from other LiDAR models using the Navier–Stokes equations and actuator disk theory.

Zhang and Zhao [120] developed a physics-guided deep learning NN model for reconstructing a three-dimension spatiotemporal wind field in front of wind turbine. Unlike previous studies that incorporated Navier-Stokes equation with predetermined parameters in modeling, the author used them for training data by integrating 3D Navier-Stokes along with LiDAR measurement as knowledge to construct a hybrid of PIML model.

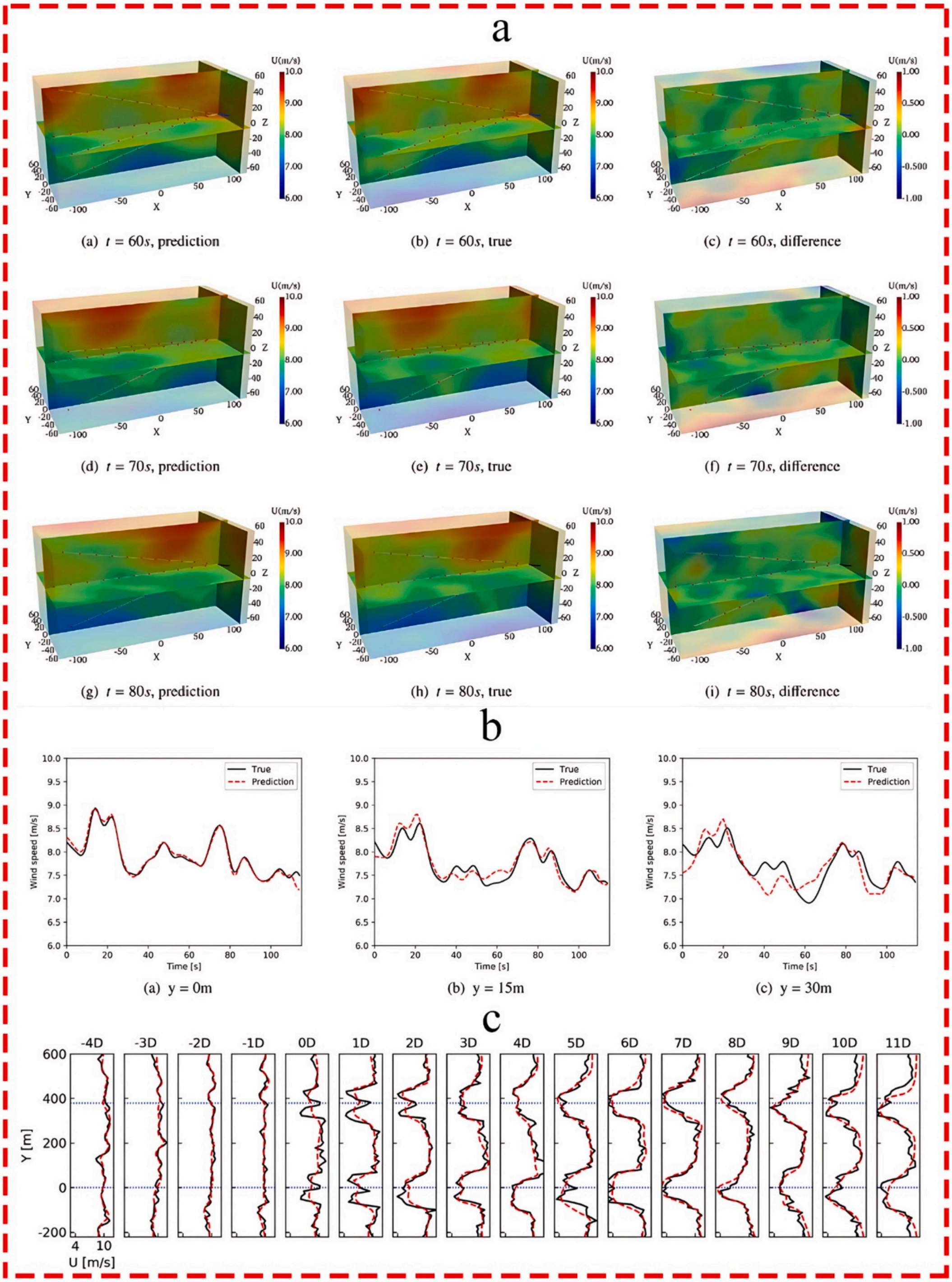

Fig. 6. a) The 3-D velocity field (visualized in *x-y* and *x-z* planes) predicted by the proposed method at time (a) $t = 60$ s, (d) $t = 70$ s and (g) $t = 80$ s. The corresponding ground truth and the difference between prediction and true flow fields are shown in the middle and last column respectively [120] Reprinted with permission form Elsevier. b) The instantaneous wind speed at turbine location predicted by the suggested PIML at the baseline case, at span-wise locations of 0 m, 15 m, and 30 m respectively [121] Reprinted with permission form Elsevier. c) The DT prediction for the greedy case at $t = 400$ s for the speed profiles [119] Reprinted from open access source.

The results showed that the model exhibited excellent performance in predicting the velocity in all directions (i.e., x, y, z), with RSME for vertical, spanwise, and streamwise velocities by around 0.361 m/s, 0.263 m/s, and 0.397 m/s, respectively, taking the pivotal parameters such as flow structure, vertical wind shear, and turbulence effects into account. Moreover, the model showed exceptional performance as it accurately predicted the flow structures, including high-speed and low-speed zones in both the x–y and x–z planes, which were validated by the actual results with minimum errors, as shown in Fig. 6a.

Similarly, in another attempt, Zhang [121] developed a physics-informed deep learning NN by total 12 layers and 128 hidden-layer by embedding the two-dimensional Navier-Stokes equation in the PIML model to address the limited sparse data provided by sensors for estimating spatiotemporal wind field, where the LiDAR data was employed as training data to overcome the Cyclops' obstacle of line-of-sight wind speed measurement of LiDAR. Interestingly, the physics-guided deep NN consisted of three sub-networks, which were collectively considered as just one NN in terms of training, as all of them share similar training variables and only one loss function. It was realized that the model offering potential enhancement for control strategy and structure load throughout the wind farm with average error for wind magnitude and wind direction by around 0.198 m/s and 2.77° in the baseline respectively. Importantly, the model showed excellent performance in capturing true value through the prediction three spanwise locations at

Table 1
Summary of PIML application in wind energy.

Objective	Dataset	ML Method	Error benchmark	Model Benchmark	Refs
Dynamic wake modeling	NREL's wake modeling via FAST. Farm	Conditional Generative Adversarial Network	RMSE	Dynamic Wake Meandering	[84]
Dynamic wake modeling	Sparse virtual LiDAR data	Neural Network	RMSE	Large Eddy Simulations (LES) results	[85]
Reconstruct wake flow field under yawed conditions	Spars Data	Neural Network	RMSE	Data-driven machine learning. (The ML model not specified)	[86]
Dynamic wake modeling	LiDAR-measured data	NN in combination of CAA and DWS	RMSE	PINN-CAA & PINN-DWS and PINN	[88]
Wind field modeling	Numerical simulation data	NN	RMSE	Actual experiment data	[89]
Dynamic wake modeling	LiDAR-measured data	Neural Network	RMSE	Linear / cubic interpolation methods	[90]
Wind farm monitoring	SCADA data + Monte Carlo simulations	Neural Network	R^2, RMSE	–	[91]
Flow field prediction	CFD simulated data by OpenFOAM.	CNN	R^2, RMSE	deep convolutional encoder–decoder networks and uNet	[92]
Spatiotemporal modeling	Numerical weather predictions + local data measurement	AI-powered Rutgers University Weather Research & Forecasting	MAE, CRPS	Not specified	[93]
Wind field reconstruction	Noisy LiDAR measurements	Residual-Connected Neural Network (RC-PINN)	RMSE	Pure PINN	[94]
Periodic dynamic induction control	LES	Physics-Informed Dynamic Mode Decomposition (piDMD)	None	None	[95]
Dynamic response of 5 MW wind turbine	Numerical simulated data by OpenFAST	Residual Recurrent NN (RRNN)	None	LSTM	[96]
Fatigue estimation	SCADA data, aeroelastic simulations	Neural Network	R^2, RMSE	Direct measurement of three turbines	[97]
Bearing fatigue estimation	10-100 turbine data	RNN	RMSE	LSTM	[98]
Sensor Fault Detection	sensor-based features	Bayesian Neural Network	Actual wind turbine sensor	LSTMs and Transformer-based models	[99]
Gearboxes fault detection	5 years of real-world data	Deep Autoencoder	Real-world data	Real-world data	[100]
Bearing fatigue prediction	Synthetic visual inspections	Neural Network	None	Shallow/deep LSTM, Actual data	[101]
Dynamic fatigue estimation	Synthetic data by OpenFAST	Traditional Kalman filter integrated with neural network	None	Kalman filter	[102]
Bearing fatigue (focus on grease) monitoring	SCADA data,	Neural Network	None	LSTM	[103]
Main bearing fatigue.	SCADA data	Recurrent Neural Network	RMSE	Actual data	[104]
Classifying anomalies in wind turbine	SCADA dataset (rear bearing temperature data)	Hybrid CNN	MAE, MSE, R^2, RMSE	RF, SVM, KNN	[105]
Cyber-attack detection	SCADA data, operational data	Isolation Forest (iForest), Physics-Based Model			[106]
Adhesive Bonds Joints fatigue	Not specified	Neural Network	MAPE, RMSE	Finite element analysis	[107]
Adaptive modal parameter estimation	Field dataset	RNN-SVD	Not specified	SVD	[108]
Wind Lifetime assessment	Real-world data	Neural Network	Long-term DEM, R^2	Not specified	[109]
Farm power prediction	Synthetic data	Graph neural network	MAPE	Data-induced GNN	[110]
Enhancing Power efficiency	CFD simulations			PID controller	[111]
Farm power prediction	Reynolds-averaged Navier-Stokes numerical datasets	XGBoost	,MAPE	LES results	[112]
Monitoring turbine performance power	SCADA data, physical model simulations	Physics-based NN, RF, SVM	R^2, RMSE	RF, Piece-wise linear regression	[113]
Power flow optimization	Synthetic data using Monte Carlo simulation	Stacked Extreme Learning Machine (SELM)	Not specified	Real-world data	[114]
Power output prediction	Real data from 4 turbines at 'La Haute Borne' farm	Neural Network	RMSE, MAPE, R^2, MAE	Actual data, Manufacturer data sheet	[115]
Load estimation	Numerical model data of IEA-15 MW turbine	CNN	RMSE, MAE	BEM model	[116]
Design of constant angles of attack blades	Numerical simulations in ANSYS	Neural Network	–	Baseline model without blade control.	[117]
Different faults detect in blades	Acoustic sensors and microphone arrays	Neural Network	R^2	CNN, MLP	[118]
Employing digital twin wind farms flow system	LiDAR measurements,	Deep Neural Network	RMSE	Actual field data	[119]
Predicting 3D spatiotemporal wind field	LiDAR measurements	Hybrid Neural Network	RMSE	Large-scale high fidelity numerical experiments	[120]
Spatiotemporal wind field model	LiDAR measurements	Hybrid Neural Network	RMSE	Actual data from wind field farm	[121]
Predicting 3D spatiotemporal wind field	Actual measured data	Neural Network	RMSE	Actual data from wind field farm	[122]

0 m, 15 m, and 30 m corresponding to the blade root, mid-span, and tip (Fig. 6b). It is worth noting that the model was limited in considering the thermal effects due to the implementation of 2D NS approach, thus, a 3D model that accounts for thermal effects would be preferable for real-world applications.

Li and coworkers [122] integrated frequency domain to PINN toward three-dimension spatiotemporal prediction of wind field. The model is utilized by important features of physical model, such as wind profiles, wind spectra, and wind field coherence functions toward precise prediction even with sparse data. The proposed model was trained with different percentage of actual measurement data which are 70 %, 50 %, 30 %, and 10 %, where the ANN and actual measurement data used as benchmark to evaluate the prediction's accuracy of FD-PINN. The 3D wind field sliced for the y-t and z-t planes, and relative errors compare to the actual measurement were illustrated for the wind field temporal evolution for four datasets from 70 to 10 % for the FD-PINN model. As it can be observed, the FD-PINN for the first three trained datasets (70 %, 50, 30 %) effectively captured (Fig-left-a-c) the non-steady-state features of the wind field over time with least errors (Fig-right-a-c), however, the errors tended to significantly increase for training dataset of 10 %.

Importantly, this is highlighted the significant role of field data in robustness of PIML models in highly complex and non-steady-state conditions.

Based on the above-mentioned studies, one important thing to be concluded is that developing hybrid PIML through integrating the Navier-Stokes equations with LiDAR measurement is a strong approach to establish a general PIML model for spatiotemporal analysis covering the whole wind farms whether for the offshore or onshore scenarios. Table 1 summarizes the application of PIML in wind energy systems.

5.2. Geothermal energy

Ishitsuku and Liu [123] developed a PINN model to estimate the distributions of pressure, temperature, and permeability in geothermal systems through integration of three loss functions including the difference between the predictions and observations ($Loss_D$), the constraint on PDEs ($Loss_{Phy}$) containing mass and energy conservations, and the boundary condition ($Loss_B$). The governing equations through the loss function guaranteed that the proposed PINN model followed rational fundamental physical principles, where it was validated by synthetic data from 2D model. Furthermore, the model's performance for an unexplored region at 500 $\leqq$ horizontal axis $\leqq$ 1000 m compared with traditional NN for predicting the temperature (T), pressure (P) and permeability (K), reported that the PINN model has substantial lower errors compared to the NN, particularly for the prediction of T and P, but marginal for K (Fig. 7e).

Yan et al. [124] proposed a PIML model to maximize the energy extraction and minimize the computational cost compared to the conventional differential evolution optimization (DEO) iterative method in geothermal systems. The model was constructed by combining an advanced hyperbolic neural network (as time-series data generator) for predicting the temperature fluid of geothermal reservoir while a control network optimized operational parameters of these estimations. Compared to DEO, the proposed framework enhanced total energy recovery by around 53.7 % and surprisingly operated faster, more than 5400 times. Moreover, the performance of PIML over DEO through optimization of the total energy (W_{ta}) across optimization iterations was evaluated. The results showed that PIML achieves the same level of maximum W_{ta} as DEO, but with just one iteration and a single forward evaluation compared to the DEO, which required nearly 20 forward evaluations for each iteration (Fig. 7b). Importantly, through employing Hyperbolic analytical function that encoded the time-series data of the produced fluid temperature the model can sustain predictions over a period of nearly 1000 years.

Qin et al. [125] combined RNN with gated recurrent unit (GRU) assisted by the numerical temporal discretization of the unknown physical equation to construct PIML, which is connected to differential equations of fluid flow to elucidate the important parameters and long-term estimation of energy production in geothermal reservoirs. The results indicated that the proposed PIML (RNN-GRU) delivered exceptional accuracy in terms of temperature prediction with RSME less than 0.06 % after 600 iterations, while the physics-guided RNN model showed reliable long-term prediction results for bottom-hole pressure, even with limited and sparse data. Importantly, the accuracy and efficiency of the model were a result of model's architecture, which took the well control variables (such as mass flow rate) as input and estimated the wells performance production (such as temperature and bottom-hole pressure) instead of the entire response of the reservoir which led to a reduction the dimension of features to learn and thus required fewer training samples.

Zhang and Li [126] embedded the PDEs of geothermal systems to the loss function of the neural networks and trained it to meet the equations along with the boundary conditions for solving the energy complex extraction of a geothermal reservoir using a closed loop ground heat exchanger. One interesting thing which, substantially improves the accuracy and the computation time, was that the author added loss weights before loss function to increase the balance of all kinds of losses, that results in the model does not focus on training one item and ignore other items. Moreover, the architecture of the coupled NN model which applied through interface conditions, allows it to simultaneously solve PDEs for both the pipe and surrounding porous media leading to eliminate the need for traditional grid-based numerical approaches. Moreover, their findings on examining the porous medium fluid flow region velocity illustrated a good agreement between the exact solution and PINN results with the increasing number of hidden layers, the model's predictions improved accordingly (Fig. 7a).

Degan and colleagues [127] compared the performance of conventional neural network with non-intrusive reduced basis (NI-RB) approach toward improving the reliability of predictions for complex geothermal reservoir and computational costs. The PIML model was constructed by using proposed method, integrated Proper Orthogonal Decomposition (POD) to capture the pivotal physical behaviors while the neural network was employed to predict the coefficients of these behaviors. Performance of both models was evaluated based on the real-world geothermal reservoir in the northern part of Germany. The results demonstrated that the computational cost for constructing surrogate models using the proposed model was 32 % lower than the traditional NN model, because of reduced dimensionality in the training data while it also delivered accurate estimations for both pressure and displacement responses. Indeed, integration of NI-RB with neural networks as an effective strategy for predicting important parameters of geothermal reservoirs has been demonstrated in other studies as well [128].

Yan et al. [129] developed a PIML model using the mass and energy balance of PDEs under the assumed condition of non-isothermal single-phase water flow in porous media and optimized with the PyTorch library deep learning which learned nonlinear relationships between input parameters such as fracture permeability and temperature fields to optimize the energy recovery of geothermal reservoir. The model demonstrated acceptable accuracy with relative errors for temperature fields and produced fluid temperatures by around 1.27 ± 0.89 % and 0.26 ± 0.46 % respectively while the sensitivity analysis of the model introduced the rate of injection as the dominant factor in thermal energy recovery. Moreover, the model showed rapid convergence for the novel control network combined with Adam (*fc*+Adam) compared to Adam itself (Fig. 7c). Besides, the model exhibited superfast computation time compared to high-fidelity simulations by about several thousand times more for *fc*+Adam compared to physics-based simulator COMSOL (Fig. 7d). Table 2 summarizes the application of PIML in geothermal energy.

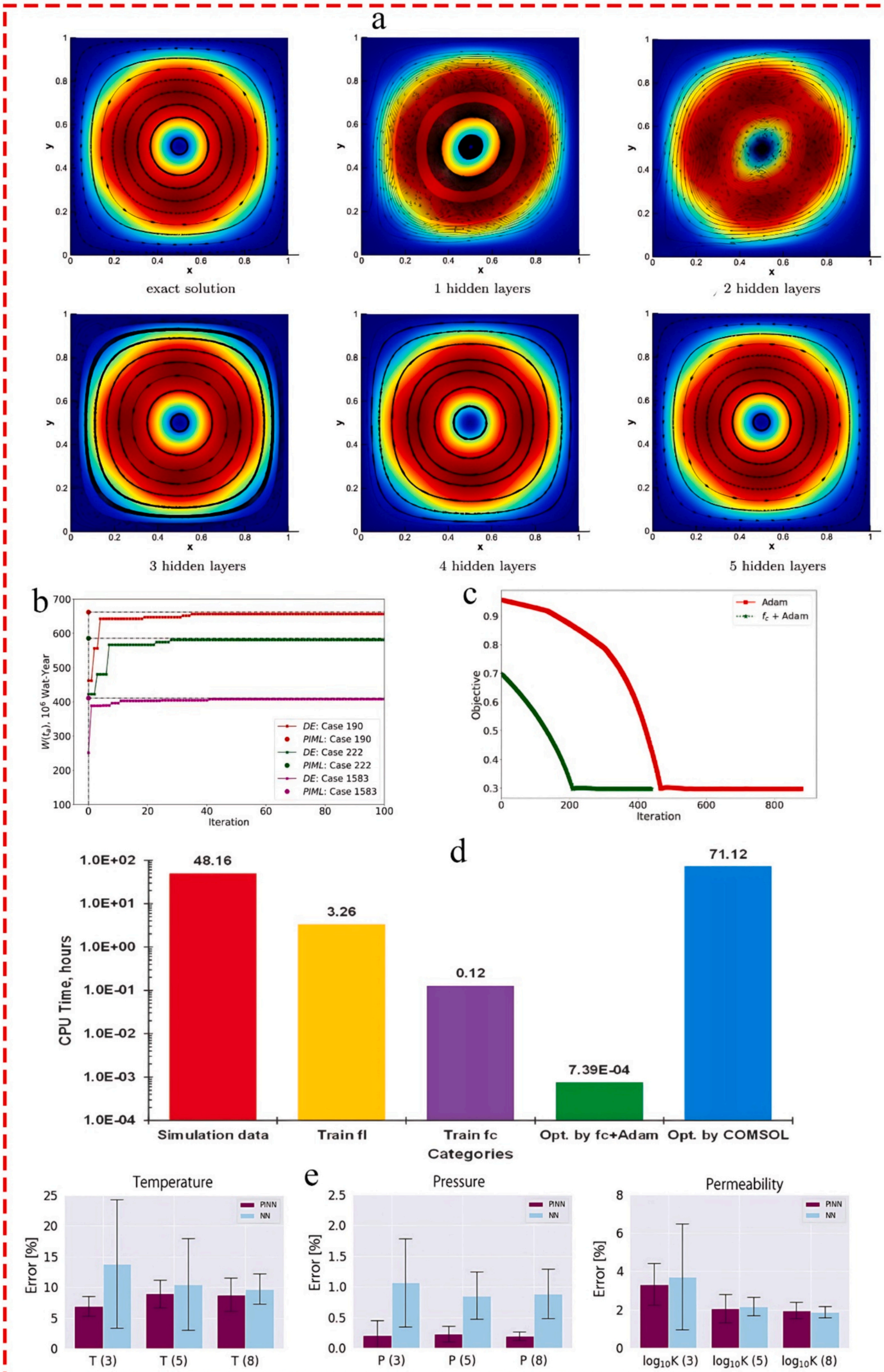

Fig. 7. a) A comparison between exact solution and neural network solution of the porous medium fluid flow region velocity [126] Reprinted with permission from Elsevier. b) Optimization of W (ta) in Exercise-2 with differential evolution (DE; iterative) and PIML (noniterative) [124] Reprinted with permission from Elsevier. c) Optimization Performance of Adam, $fc + Adam$ for different cases [129] Reprinted with permission from Elsevier. d) The CPU time of different parts for optimization [129] Reprinted with permission from Elsevier. e) Prediction errors of the PINN and NN for the interpolation and extrapolation horizontal ranges with different numbers of wells. for temperature (T), pressure (P), and permeability (K) at the interpolation horizontal interval (500 ≦ horizontal axis ≦ 1000 m) [123] Reprinted from open access source.

Table 2
Summary of PIML application in geothermal energy.

Objective(s)	Parameters Optimized/Predict	Type of ML Method	Dataset	Error benchmark	Model benchmark	Refs
Predicting geothermal properties	Temperature, pressure, permeability	Neural Network	Synthetic 2D models	RMSE	Conventional neutral network	[123]
Optimizing geothermal reservoir management	Predicting total energy production + fluid temperature	Neural Network	Synthetic data	RMSE, R^2	Differential evolution	[124]
Estimating energy production	Temperature, pressure	RNN	Simulated dataset	RMSE	Gated recurrent unit	[125]
Ground heat exchanger performance	Temperature, fluid flow, heat transfer	Neural Network	Numerical results	–	Exact solution	[126]
Develop reliable surrogate geothermal models	Pressure	Non-intrusive reduced basis, Neural Network	Simulation data	–	Conventional NN, FEM-Simulation	[127]
Compare PIML methods in geothermal simulations	Pressure, Displacement	Non-intrusive reduced basis, Neural network	Synthetic data	Difference between simulation & prediction	Estimate state NN, Parameter Estimation NN	[128]
Optimize reservoir management in geothermal systems	Temperature, produced fluid temperature, injection mass rate	CNN, (PyTorch library utilized)	Synthetic data	Difference between simulation & prediction	COMSOL results, Simulation data	[129]

5.3. Biomass energy

Bibeau et al. [130] developed a physics-informed neural network (PINN) model to estimate the reaction kinetics of producing biodiesel using a microwave reactor to understand the rates of reaction of a transesterification process where glyceride is one of the main products. The PIML model was constructed through a hybrid integrated mode by combining physical model through ordinary differential equations (ODEs) and trained with limited data from several experiments of canola oil transesterification and the main equations (Arrhenius equations) for three different power input values to predict concentration and temperature were developed. It was concluded that the model recognized the constant rates and their temperature dependencies while it successfully predicted the concentration profiles of monoglycerides, diglycerides and triglycerides.

Bangi et al. [131] proposed a PINN to reveal the kinetic mechanism behind producing β-carotene by employing *Saccharomyces cerevisiae* through fermentation method. In the first step they developed a simple kinetic model to illustrate the strength in predicting the accurate values. Hence, the universal differential equation (UDE) integrated with ODE to capture the hidden dynamic parameters in the fermentation, and batch fermentation experiments were used to build the PINN. The strength of traditional kinetic models based on three parameters evaluated by acetic acid, β-carotene generation and biomass, was compared with experimental data, showing that the accuracy of the kinetic model for predicting biomass, acetic acid, and product concentrations was not satisfactory (Fig. 8b), in contrast to the PIML which well predicted the process. This is due to the architecture of PINN as the neural ODEs in the UDE-based hybrid model were trained to capture the hidden dynamics of the process which were not considered in the kinetic model. Although the PINN model delivered an accurate model for predicting kinetic reaction, it was emphasized that the training data must be noise-free which could be limiting factor in developing accurate models considering the variable nature of biochemical reactions.

Ren et al. [132] developed a PIML model by combining synthetic data along with actual experiments through ANN for estimating the composition of the produced syngas (Nitrogen, hydrogen, carbon monoxide/dioxide and methane) during biomass gasification process and compared the model with five conventional ML models (RF, SVM, ANN, gradient boosting regression -GBR-, and XGBoost). The suggested PINN was incorporated by regression, structural, and physical monotonicity constraints within the loss function and trained with more than 320 experimental data. Particularly, synthetic samples were constructed and injected with special monotonicity features within the PINN. To evaluate the strength of the models, the variation of hydrogen content with increasing temperature for all scenarios was compared. The red dots (shown in Fig. 8c) represent selected experimental samples, and all six models approximate the data with minimal error. As seen in Fig. 8c (i–iii) the three tree-based models produce step-like curves where H_2 remains constant despite significant temperature changes, while it followed by abrupt jumps, which indicate a failure to reflect the expected monotonic trend. The SVM and ANN models Fig. 8c (iv and v), however, exhibited yield smoother curves but still could not fully capture the correct monotonic behavior. Conversely, it can be observed in Fig. 8c (vi) the PINN model predicts a consistently increasing H_2 with temperature, aligning well with the true physical relationship.

Darlik et al. [133] integrated the Navier-Stokes and continuity equations into the NN's loss function and provided training data to develop a PINN model to overcome the limitation of Discrete element-CFD method in predicting behavior of biomass particles (velocity, pressure, and density fields) within a moving chamber reactor. Importantly, they regarded the biomass particle as continuous fluid for simplicity of the modeling. The results showed that the PINN model error compared with Extended discrete element method (XDEM) numerical results were less than 2 % where time-based mean squared error for velocities, pressures, and densities decreased significantly over simulation time with the range of 10^{-6} - 10^{-3}. However, one of the limitations of the model was the assumption of particles as a high dense medium like a fluid, restricting the prediction of particles behavior in less-dense regions of the chamber.

Hosseini et al. [134] proposed an architecture of PIML by implementing Bratu Equations (governing equation of chamber) PDE's within neural network for modeling biofuel production. The critical idea was to utilize the loss function by incorporating the underlying physics (i.e. the PDE) within the NN architecture. The PIML model was compared with conventional numerical approaches such as Laplace and decomposition methods in terms of maximum absolute errors where the findings indicated that the model outperformed both approaches accordingly. The proposed model showed faster convergence and optimization in solving nonlinear dynamic equations, making it an appropriate option for real-time analysis of the biofuel combustion modeling. However, the model's high dependency on high-quality training data makes it prone to limitations in complex environments.

Ren and co-workers [135] implemented disentangled representation learning PINN in a comparative study with traditional PINN model to estimate the generated biogas compositions in a biomass gasifier chamber. The model was integrated with variational autoencoder to extract relevant features from high-dimensional feedstock properties while synthetic sampling utilized in the latent space to ensure a diverse representation of feedstock types during training. The model exhibited exceptional outcomes when compared with traditional ML models like RF, GBR, SVM, and ANN. As can be seen, the performance of the model in examining the relationship between H_2, temperature (T), and equivalence ratio (ER) for a specific feedstock type of the training set was evaluated against other models. The contour lines represent the molar fraction of H_2 with T and ER displayed on the horizontal and vertical

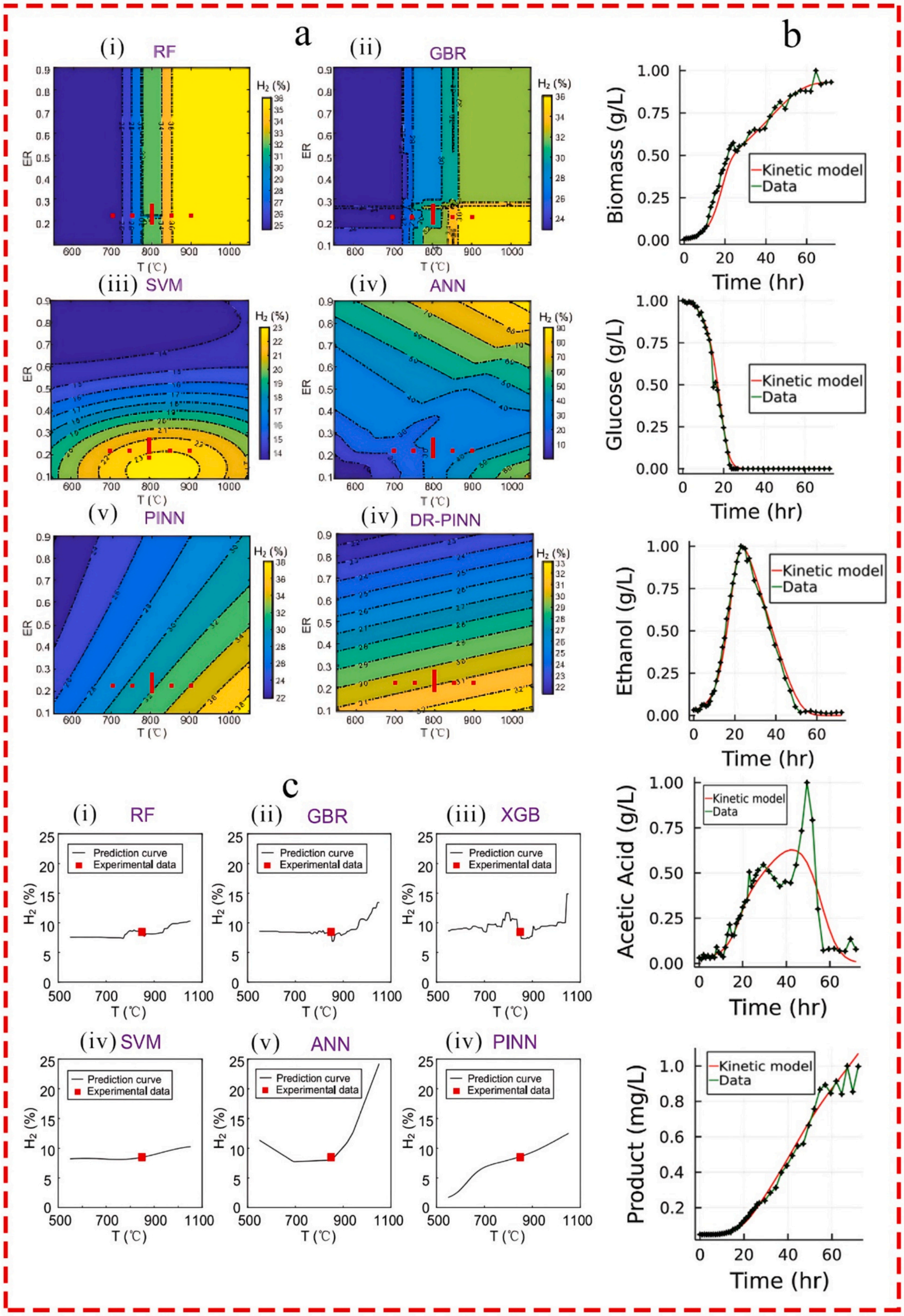

Fig. 8. a) Two-way partial dependence plot of six ML model from top to bottom RF, GBR, SVM, ANN, PINN, and DR-PINN for the H_2 in the training set for learned biomass types [135] Reprinted with permission form American Chemical Society. b) Comparison of predictions from kinetic model against the experimental data for an initial glucose concentration of 20 g/L [131] Reprinted with permission form Elsevier. c) Comparison of One-way partial dependence plot of the H_2 [132] Reprinted with permission from Elsevier.

axes respectively. Red squares mark the actual experimental data points for this feedstock. Fig. 8a (i–iv) demonstrates that RF, GBR, ANN, and SVM fail to capture the correct monotonic trends of both parameters. In contrast, Fig. 8a (v–vi) shows that the predictions from DR-PINN and PINN increase consistently with T and decrease with ER which is aligning well with physical expectations and suggested strong interpretability for both PINN-based models. Furthermore, the DR-PINN model obtained high predictive accuracy for in-sample and out-of-sample feedstock with RMSE an R^2 by around 0.96, 0.81 and 1.7 % and 3 % respectively.

Indeed, the significance of the model lies in implementing a Variational Autoencoder (VAE) – a common method to achieve disentangled representations – through its unique feature that transfers the original data into a latent variable space in the form of a probability distribution to achieve a disentangled representation, which, in other words, decomposes an original data set into independent subspaces, where each subspace does not affect the others, reflecting better interpretability and generalizability. It is important to note that, the significance of implementing PIML methods in biomass energy recently brought into the spotlight by some researchers. For instance, Pascarella et al. [136] in a study on biomass pyrolysis using various machine learning models, such as XGB, MLP, SVR, RF, and Mixture of Experts (MoE), emphasized on the importance of developing explainable ML models by using physics-informed approach. Table 3 summarizes the application of PIML in biomass energy.

5.4. Solar energy systems

5.4.1. Flat plate solar collector

Han et al. [137] combined a physics-guided ML with numerical simulation, a geometrical regenerative algorithm and constructal theory to optimize the thermal performance of a flat plat solar collector considering the variation of solar intensity and ambient temperature with alumina nanofluid as the medium inside the solar collector. The PIML model was developed based on an architecture integration mode by implementing PDEs under transient multiphase flow during a day with a liquid–particle model for the nanofluid into the neural network while the constructal theory was applied to find optimal geometry values. They assumed various scenarios including a wide variation for number of pairs and clusters, about $1 < Np < 10$ and $1 < Nc < 30$, respectively. The findings showed that the thermal efficiency of the system was substantially improved, with the highest T_out for solar collectors obtained at $Nc > 3$ and $Np > 5$ (Fig. 9a). However, it should be reminded that employing a point cloud method as 3D modeling approach along with NN and constructal theory results the proposed PIML analyzed over 186 million data points in 63 series to determine the optimum range for Np and Nc, which could be considered as a high computation cost.

Importantly, geographical location and climate such as conditions in high-altitude regions particularly in mountainous regions significantly impact the performance of solar energy systems [138–140]. In his regard, Cáceres et al. [141] in a comparative study, developed a PINN for a flat plate solar collector in Andean highlands of Ecuador to predict the performance of thermal performance of collector. The PINN was developed in an integration mode by embedding synthetic simulated data into a well-established thermodynamic model of solar collector. While the PINN demonstrated close agreement with the thermodynamic model (heat loss coefficient 5.199 vs 5.189 $W.m^{2}\cdot K^{-1}$), the strength of the PINN was highlighted by its significantly different forecast of the collector outlet liquid temperature (55.05 °C vs 67.22 °C from the thermodynamic model). Although this highlights the power of PINN in capturing the behavior of system in a complex environment, one important thing to be reminded is that the PINN was trained with generated synthetic data which could be considered as a potential source of error in more complex solar energy systems.

5.4.2. Photovoltaic

In several studies, physics-based approaches were employed to provide training data and compare the performance of different ML models [142]. For instance, Pombo et al. [143] used physics-informed approach as a feature selector to evaluate the effectiveness of several ML models, including RF, SVR, LSTM, CNN and a combination of CNN-LSTM, toward forecasting PV performance. The features selected by the physic-informed approach were compared with those from another well-established approaches, Pearson method. The findings showed that dataset expansion approach combined with a physics-informed feature selection contributes to simpler training and more accurate predictors. Moreover, it was examined that the RF model, terms of RSME, and MAPE, and R^2 with 11.7 % and 18.6 % and 0.94 respectively, outperformed than other models (Fig. 9d). More importantly, it was shown that all ML models assisted by physics-based approach have higher accuracy and lower computation time because the physic-based approach reduced the search-space and eliminated redundant parameters, resulting in better performance than Pearson.

Jannik and co-workers. [144], compared the robustness of two deep learning methods based on CNN and physics-informed CNN for fault detection tracker in solar PV power plant. To evaluate the performance of models, the authors applied two types of data within models which are synthetic simulated data and data from actual PV plants, under operating faulty data among both datasets. The findings showed that when the model was run based on synthetic data physics-based model resulted in better predictions on fault tracking than the other, but the CNN still delivered an acceptable value (0.99 vs. 0.93). In contrast, when the models were run with actual operational PV plant data the physics-based model exceptionally outperformed than the pure CNN, almost the same as the first scenario. This highlights an important point that when data-driven model assisted by physical information about the fault mechanism, this knowledge allows the model to generalize much better from synthetic to real faults. In an interesting study, Jahangir and Alam [145] developed a PIML model for predicting PV farms which could be applied throughout the world. In this regard, they divided the world into four main parts for planet-based evaluation of the PIML model. At first, the model trained with only 5 specific but very accurate dataset from the United States, and the tested results showed remarkable accuracy in predicting PV performance in other locations throughout the world. In the second step, the PIML model trained by 3000 datasets gathered from different locations which were considered as heterogeneous data, and it reported high accuracy for predicting yearly output of PV in different locations (US and India). They selected diverse samples of data from the big dataset to check the strength of accuracy and diversity of sample on

Table 3
Summary of PIML application in biomass energy.

Objective	Type of ML Model	Dataset	Error Benchmark	Model Benchmark	Ref
Predict biodiesel reaction kinetics in microwave reactors	Neural Network	Experimental data	MSE	Numerical ODEs results	[130]
Hybrid model for β-carotene production in fermentation	Neural Network	Experimental data	MSE	Kinetic models	[131]
Predict syngas compositions in biomass gasification	Neural Network	Experimental data	RMSE, R^2	RF, GBR, XGB, SVM, and pure ANN	[132]
Simulate biomass particle fields in combustion chambers	Neural Network	XDEM	MSE	Numerical data of XDEM	[133]
Solve Bratu equation for biofuel combustion	Neural Network	Experimental / Simulation data	MSE	Exact solution, Laplace, Decomposition	[134]
Predict biomass gasification syngas with DR-PINN	DR-PINN with VAE	Experimental data	R^2	Not specified	[135]

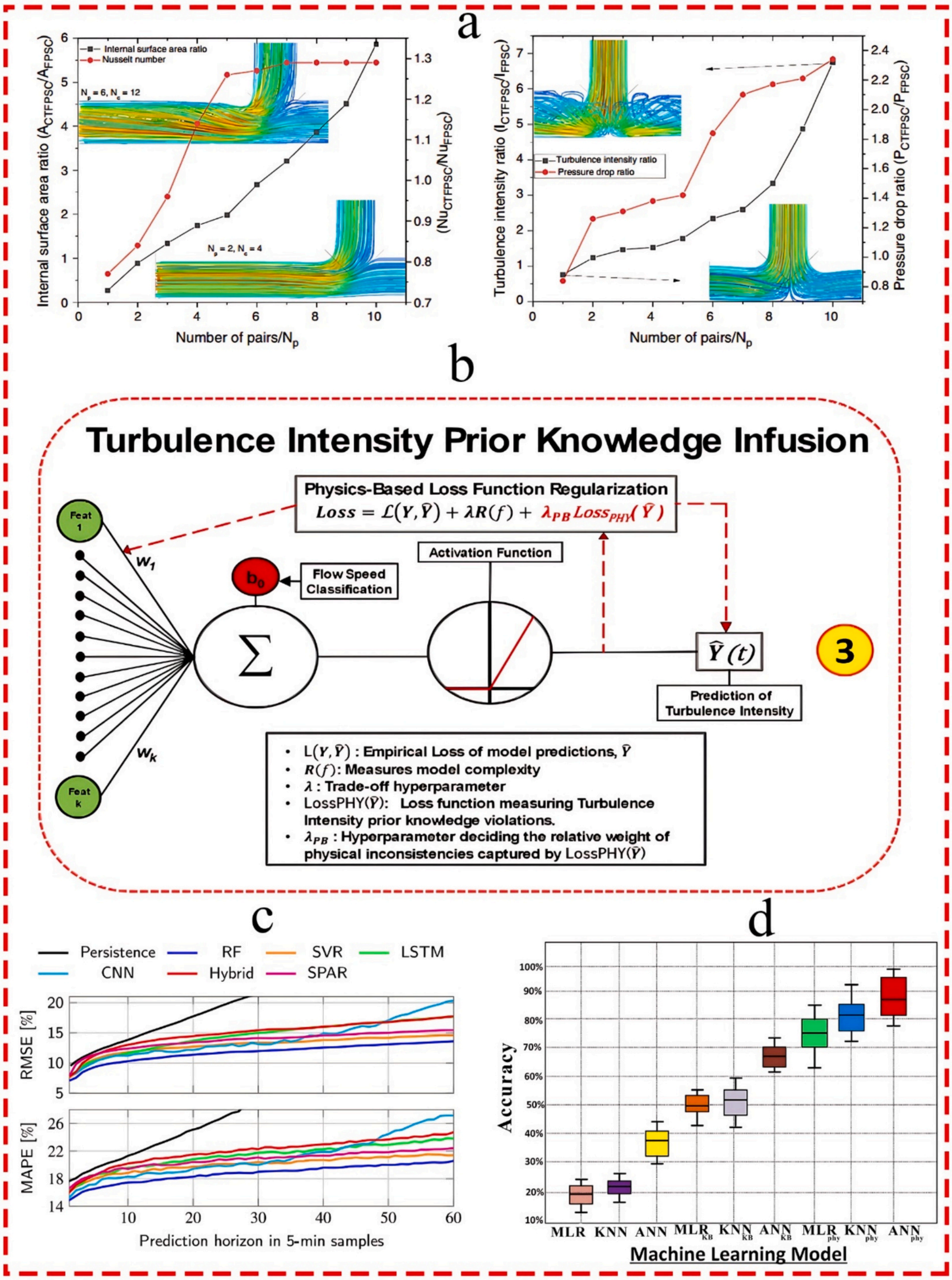

Fig. 9. a) Variation in Nusselt number ratio with Np and internal surface area ratio (Left), and pressure drop and turbulence ratio with Np (right) [137] Reprinted from open access source. b) Schematic detailing how a key physical relationship existing between T.I. and *Ps*(*t*) are leveraged to construct a physics-based loss function. Time-domain features characterizing *Ps*(*t*) are fed into a feed-forward neural network. During training, a physics-based loss term is appended to the loss function of the neural network to penalize T.I. classifications that violate the physical relationship existing between T.I. values and *Ps*(*t*) [149] Reprinted with permission from Elsevier. c) Comparison of the best errors for different ML model [143] Reprinted from open access source. d) accuracy of different machine learning algorithms comprises of purely data-driven (MLR, KNN, and ANN), prior knowledge integration approaches (MLR*KB*, KNN*KB*, and ANN*KB*), and physics-guided approaches (MLR*Phy*, KNN*Phy*, and ANN*Phy*) [149] Reprinted with permission from Elsevier.

models' performance and reported very accurate results comparable with the PIML trained with the big dataset. These findings highlighted an important point about the role of datasets in PIML: if a smaller dataset diversely sampled, it contains sufficient information to make global-scale yearly yield predictions.

Apart from using PIML in large-scale PV system, several researchers also applied PIML for examining the PV systems in micro-scale, such as understanding short-circuit current and open-circuit voltage [146].

For instance, Wang et al. [147] developed a physics-guided CNN model for estimating the connective heat transfer of PV cell and compared the results with two conventional empirical and CFD models. The PIML was trained with 160 CFD datasets, however, as two important inputs (length and height) in the model were essentially non-physical and the model was developed based on the geometry of PV, they incorporated physical laws directly into the loss function be more interpretable regarding the Nusselt number. The suggested PIML model exhibited marginal errors of 2.5 % and 2.7 % on the validation and testing datasets correspondingly. Moreover, the model elucidated how the architecture of PV arrays in rows (in a 10-row PV panels) affected power production where the first three rows outperformed while from the fourth row a substantial reduction in heat transfer efficiency was observed.

In another study [148], Zheng's group implemented the ODEs in PIML and corrected the predicted PV temperature to precisely predict the power output of the panel over a long period of time in all seasons. The authors evaluated different ML models such as RF, LSTM, CNN, bidirectional-LSTM and method called Long-short term cross attention mechanism (LSCAM) in PINN and embedded the heat balance equation into the loss function. The findings showed that the combined model based on PINN+LSCAM performed well, through all seasonal test datasets delivered the most concentrated and narrow residual distribution leading to the highest prediction accuracy in all metrics (R^2, RMSE, nRMSE) and stability compared to all scenarios. Table 4 summerizes the application of PIML in solar energy.

5.5. Ocean current energy

Converting kinetic energy of ocean currents to electricity by a turbine is one of the cutting-edge and promising approaches toward renewable power generation. Freeman et al. [149] proposed a novel fault detection framework for marine current turbine (MCT) rotor blades that integrated PIML to enhance fault detection accuracy. Explicitly, they integrated both the physics-based prior knowledge of the oceanic environment and the turbulence intensity (T.I.) time-domain features into the ML pipeline of a neural network. The T.I.-based prior knowledge incorporation was made via the inclusion of a physics-based loss function, to ensure that model predictions remain scientifically consistent with the underlying physics of MCT as illustrated in Fig. 9b. Specifically, by incorporating environmental condition data with non-intrusively acquired electrical power signals from the turbine, the main aim of framework was to utilize a PINN with a physics-based loss function with incorporating hydrodynamic rotor dynamics. The model process's fault features extracted from electrical power signals and environmental data to detect rotor blade imbalance faults. The model achieved a Type-I error (false positive) rate of 5 % and a Type-II error (false negative) rate of 2.92 % and demonstrated great improvements in fault detection compared to conventional processing methods. Importantly, the hybrid PIML model with the inclusion of environmental parameters such as current flow velocity and turbulence intensity, when compared with traditional approaches like Multinomial Logistic Regression, K-Nearest Neighbor (KNN) and ANN exhibited superior performance with the highest accuracy. However, one of the limitations of the study was that it mainly relied on simulated data rather than real-world data while the model has not been validated with real-world operation data, making its performance questionable under real conditions.

5.6. Hybrid renewable energy systems

Osorio and co-workers [150] developed a PIML based on extreme theory of functional connections (X-ETF [151]) for predicting energy efficiency and heat transfer in a solar thermal power plant on the basis of empirical correlations. Unlike the conventional data-driven models, the proposed model didn't rely on offline training with large amounts of historical data, conversely, it utilized physic-based engineering knowledge of the thermal plant itself which was expressed through a set of differential equations. The model simulated seven days of plant operation in just a few seconds without propagating errors, because the algorithm works iteratively on each subdomain and updates initial conditions with every new data set. Interestingly, the model further validated for its accuracy under actual thermal power plant condition with real world data for estimating energy efficiency and heat transfer of tank and delivered errors as low as 0.1 %. It is worth noting that this architecture is not only capable of enabling the proposed PIML for online and real-time prediction of the system from weather conditions inputs, but it can also be applied to other thermal plants simply by adapting the underlying physics-based model.

Pombo et al. [152] proposed a cogeneration power plant for producing power and drinking water consisting of solar PV, wind turbine,

Table 4
Summary of PIML application in solar energy.

Objective	Parameters Predicted /Optimized	ML Method	Datasets Used	Error Benchmark	Model Benchmark	Refs
Enhance thermal efficiency of flat plate collector	Thermal efficiency Outlet temperature, Heat transfer	Neural networks	Synthetic data	MAE, R^2	Numerical simulations	[137]
Estimating overall performance of solar collector	Heat transfer coefficient, Outlet temperature	Neural networks	Synthetic data from Thermodynamic models	MAE, R^2	Experimental Data	[141]
Increase in accuracy of solar power forecasts	Hourly solar power output	Physics-based RF, SVM, CNN LSTM, hybrid CNN-LSTM	Not specified	MAE, RMSE	Experimental Data	[142]
Short term PV performance	PV power output, Forecasting accuracy	RF, SVM, CNN LSTM, SPAR, CNN-LSTM	PV power, weather data from a PV system in Denmark	RMSE, MAPE, R^2	RF, SVM, CNN LSTM, hybrid CNN-LSTM	[143]
Tracker fault detection of PV	Tracker fault presence, Operational status	CNN	Real operational data and synthetic faulty data	RMSE	Referenced model	[144]
Global solar farm modeling	A unify model for different locations	Neural Network	Synthetic datasets, Public sparse and heterogenous data	RMSE	Physics-based simulations	[145]
Predicting Organic Solar cells efficacy	Short-circuit current, open-circuit voltage, fill factor	Model developed: 5dimensional (5D) equation produced by SISSO	Synthetic datasets	MAE, RMSE	Gradient boosting Models	[146]
Estimate convective heat transfer for PVs	Heat transfer coefficients, Temperature	Deep Convolution Neural Network	Data generated from 160 CFD simulations in COMSOL	MAE	Empirical method, CFD model	[147]
Predicting PV power output for all seasons	Cell Temperature, Power output	Neural Network + Long-short term cross attention mechanism (LSTCM)	Real-world data	RMSE, R^2	DNN + LSTM, LSTM, PINN-LSTM, PINN + *Bi*-LSTM, PINN + CNN-LSTM	[148]

small nuclear plant, reverse osmosis plant and multi-stage flash desalination. The mix linear integer programming (MLIP) was employed for optimizing the power plants inputs namely electrical and thermal while two PIML methods, RF and combined CNN-LSTM, were applied to predict the availability of renewable energy with residuals fitted to statistical distributions to characterize errors end were trained using the Solar Energy Testing and Evaluation (SOLETE) dataset. The findings showed that through MLIP the renewable curtailment was minimized to 3-4 % during high solar intensity availability days, while it reached 8-10 % curtailment on lower availability days. Importantly, it should be mentioned that the PIML model does not have a significant impact throughout the modeling and is only used to predict the available power form renewables. It was found that the R^2, RSME, and MAPE for solar power and wind power stand at 0.94, 0.98 and 8.9 % as well as 22.45 %, 14.6 %, and 29.3 % respectively while for hybrid CNN-LSTM they were 0.89, 0.98 and 6.1 %, 24.7 % and 10.9 % and 28.01 % correspondingly. Regarding these values, it is somewhat bit complex to make a decision on selecting the best ML model.

Pombo [153] employed the PIML based on RF and CNN-LSTM for co-locating solar PV and wind farms in an integrated design and used SOLETE dataset to train the model. The models were compared with conventional Pearson-based feature selection where both PIML methods outperformed than the conventional method. The RSME and MAPE values for both models were the same, however, the R^2 values were insignificantly better for CNN-LSTM rather than RF for solar and wind power, at approximately 0.95, 0.96 and 0.95, 0.94 respectively. However, one of the limitations for both studies was the models relied on the SOLETE dataset rather than real data. This can make model validation challenging for real world applications, particularly when the renewable systems are aimed at providing power for an energy system like cogeneration power plants.

Collectively, it can be observed in Fig. 10 that the PIML is extensively applied in wind energy systems with biomass and geothermal energy contribution being almost equal. However, the lowest share of PIML application is for the ocean current energy conversion due to the novelty, early stages of development, and the complex environment of this technology.

6. Criteria and indictors for selecting PIML methods

As mentioned above, a wide range of PIML approaches could be implemented to solve different problems in RESs. However, based on the type of problem and adopted strategies in solving the effectiveness of models can vary case by case. Therefore, an initial nuanced point is to implement at least two different methods in PIML if there are no criteria and indicator for selecting the proper method. Of great importance, several indicators and criteria could be selected to weight the model. Accuracy of the developed model is one of the easiest ways to understand the effectiveness of a model which can be evaluated through standard machine learning metrics like RMSE, MAE, TE. Since real-world data often are noisy and uncertain, another indicator is the robustness of model in handling these types of data while at the same time it maintains consistency and could be generalized accordingly. Another important criterion which can represent a powerful model is transparency and interpretability. Indeed, a powerful PIML model should elucidate the relationships between input variables, physical laws, and outputs to be applicable for real-world applications. Another pivotal indicator in selecting a powerful PIML is computational efficiency and scalability of model for complex and multi-dimensional problems. In this regard, the training time and real-time performance and the speed of PIML models that generate results directly impact computational cost, which is vital in selecting a high-performance method. One of the key advantages of PIML is that it can provide more interpretable models that align with physical understanding. Hence, one of the strengths of highly efficient models should be allowing for the extraction of physical insights such as identifying dominant physical phenomena (e.g., turbulence vs laminar flow or heat transfer mechanisms).

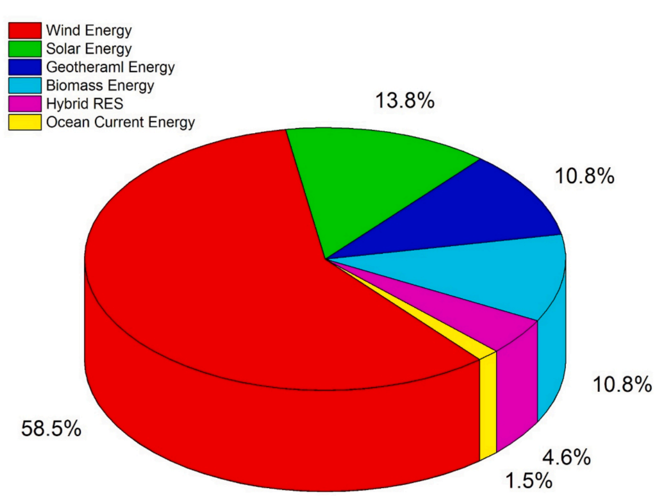

Fig. 10. The share of PIML in various renewable enregy systems.

7. Future perspectives (What's next?)

In a nutshell, it is obvious that the application of PIML in specific RESs such as wind energy has explored more opportunities compared to other renewable resources like biomass and geothermal energy. This can be attributed to several factors regarding the nature of wind energy as a well-established and high potential renewable system. Indeed, wind energy is leading renewable source in the renewable energy market throughout the world and has a lot of success stories. Besides, the technology in this sector has reached maturity, and a lot of investments have been allocated by the superpower governments like China, foreign government investment in low-income countries and even investment in private households [154–156], to the sector which makes it important in the policy of energy experts and brings the support of incentives behind the technology. Finally, it is important to note that the abundant availability of data in wind energy systems and the obstacles faced by the industry for exploiting the maximum energy, make the predictive challenges leading to more research in this field. On the other side, other technologies such as biomass and geothermal have not spread globally and do not have the above-mentioned factors that wind energy has, which can be considered the reasons why the number of studies in other fields is limited. Moreover, some renewable systems like ocean current energy or hybrid renewable are too novel and still in their infancy stages, which could explain why limited studies have been done on these topics. However, one interesting observation which can be noticed is that, even though solar energy is the second renewable energy source in the renewable energy market, and it has numerous applications from desalination, power generation and hydrogen production to environmental applications, it has not received sufficient attention in the context of PIML studies and only five studies have been conducted.

Based on the above discussions on PIML in RESs, the following can be extracted as the future directions:

- **Wind Energy**: For wind energy many studies focused on fatigue estimation or wake field reconstruction, are limited to the specific turbine and controlled environmental conditions, however, it is vital in future research to develop a model that can be generalized across various turbines as well as environmental conditions. Indeed, this highlights the importance of scalability as one of the cornerstones for future studies of PIML in wind energy to develop models that can be extended to the entire wind farm. Moreover, the current state-of-the-art is mainly relies on simulated and historical data; though it is considered as a good step in this field it is recommended for future research to integrate real-time data with PIML toward dynamic optimization, this approach can provide useful insights into real-world problems that the systems might face. Furthermore, combining the advanced control strategies such model predictive control into PIML can be considered another avenue in this context. Applying such strategies in the future could result in advanced research in the context of PIML in wind energy by developing more complex models that are capable of adaptation and self-learning. Interestingly, all studies on applying PIML in wind energy have outshone the performance of system from technical point of view; however, combining economic analysis as well as environmental aspects could provide forward-looking insights from economic and environmental perspectives in the long-term operation of a wind farm.

- **Solar Energy**: The limited number of studies on solar energy applications have been performed on flat plate solar collector and photovoltaic and focused on the layout configuration and prediction/optimization. However, a huge body of knowledge in the application of solar energy has been unexplored both in small-scale and large-scale schemes. For instance, concentrated solar power (CSP) towers are one of the main large-scale solar-driven power generation systems which need a very accurate and detailed design, specifically for those that operate with molten salt. Hence, one interesting research gap in this field could be examining the PIML in CSP for both mediums oil and molten salt, particularly for long term operation. Another large-scale application is the solar pond, which has several successful practices throughout the globe, but faced with obstacles in long-term operation such as salt crystallization, formation of various zones for storage and insulation, just to name a few. By coupling the heat and mass transfer equations to ML methods and considering the plenty available data from previous large-scale studies, feasibility investigation of salt gradient solar pond through PIML for different regions could replace old models. For small-scale applications, solar still and interfacial solar evaporators, as two well-established and important methods for providing safe drinking water, can be considered as an attractive research gap, regarding the huge number of studies and experiments conducted in this field. However, it should be noted that PIML in this context could be employed for prediction and optimization to overcome one of the main obstacles of interfacial solar evaporators for practical implementation in the long-term operation.
- **Biomass Energy**: For biomass most PIML methods have employed the neural network and did not take advantage of other ML approaches. Although, the NNs have proved to be one of the most powerful ML methods, it is recommended for future research that PIML for evaluating any aspect of biomass energy (whether for kinetic reaction modeling or predicting influential parameters) be compared with other ML methods, with particular interest in deep learning approaches. Moreover, plenty of suggestions for future research on PIML could be proposed in biomass energy such as bioreactor design, feedstock optimization, products (and by-products) prediction, reaction optimization etc., since the number of studies in this context are in early stages. Regardless of any aspects of biomass energy that future studies address, one important thing is to conduct research considering the large-scale application. Moreover, oversimplified assumptions such as considering the behavior of biomass particles in a bioreactor as a fluid, could generate inaccurate results, leading to precise prediction only in specific regions; therefore, it is highly recommended for research to develop PIML model without oversimplified assumptions that applied across all domains. Last but not least, there is the problem with available data since the inconsistency in existing data is commonly problematic, issue not only in biomass but also in other renewable energy systems.
- **Geothermal Energy**: Due to the nature of this category, where the source of energy is not readily available and requires specific instruments, the pivotal role of data could be brought more into the spotlight. That said, it is critically important that a comprehensive dataset containing simulated, synthetic, and real-world data be gathered all in a framework, because most studies heavily rely on synthetic and/or simulated data. Current PIML models in the existing literature need to be integrated with other disciplines because the current models mainly focus on thermal analysis and fluid flow, making it crucial to incorporate more physical phenomena, like chemistry and geology. This makes the PIML development in geothermal energy systems very complex, but at the same time there are many opportunities for future research. Moreover, the studies in this context focus primarily on power prediction and optimization, while the application to fault diagnosis has not been highlighted. Therefore, another interesting research direction in this context could be the use of PIML for health management of geothermal energy systems.
- **Ocean Currents Energy**: This technology is quite new and still at the laboratory-scale. Although numerical and experimental studies have been conducted [157,158], the technology needs to be further established, which means that the problem of limited and sparse data in this technology is more visible. Therefore, PIML in this field can greatly assist researchers in generating useful datasets for future development, since there are limited studies that have employed PIML in ocean current energy conversion. Moreover, implementing PIML could enhance simulation accuracy by integrating sparse observational data and governing physical equations to enable a better understanding of flow interactions with marine turbines, while facilitating efficient design iteration by combining CFD with PIML-based surrogate models to lower computational costs. Interestingly, by observing long-term ocean current patterns, energy density, and bathymetric features, future PIML-based research can be used for site selection of marine turbines, where PIML merges historical data and physical constraints to predict site-specific energy potential and identify and evaluate the most viable sites for turbine deployment. Similar to wind energy, a pivotal future direction in this context is ensuring the structural integrity and longevity of turbines under operational loads, such as predicting blade stress, fatigue life, vibration modes, and hydrodynamic forces. In this regard, complex models in PIML can examine interactions between mechanical loads and environmental conditions to support proactive maintenance through early failure detection.
- **Hybrid Renewable Energy:** The approach of hybrid systems is more conceptual than practical. Although there is a large body of research on integrating different renewable systems [159], PIML has only been applied in solar–wind integrated systems. Therefore, a next step for future research could be applying PIML to other integrated renewable energy systems such as solar–geothermal, solar–biomass, and solar–wind–biomass. However, these systems still lack large-scale practical applications, with only a few small-scale prototypes tested so far.
- Based on the application of PIML in RESs, NNs and DL algorithms have contributed to the highest number of studies, whereas other ML algorithms (i.e., ensemble and classical approaches such as SVM, SVD, RF, XGBoost, etc.) have been applied far less frequently.
- Among the well-established DL methods in PIML, CNNs appear to be an attractive choice across all RESs, particularly in wind energy, due to their inherent capability of processing fixed inputs and generating fixed outputs. On the other hand, RNNs, with their different architecture, which allow variable inputs and outputs, have also been applied in several studies. Thus, one important consideration is to select the appropriate DL method based on the nature of the problem (e.g., extracting features using spatial hierarchies vs. processing sequential data using information from previous steps) and the available type of data, depending on the RES in question.
- The most well-known merit of PIML is the robustness of models when dealing with sparse and irregular datasets, achieved by

implementing governing equations that enforce physical consistency and avoid non-realistic outputs. This integration enables accurate surrogate models of computationally expensive simulations, such as CFD or multiphase flow, while reducing data and computational demands. Together, these features enhance the predictive accuracy of PIML compared with classic ML across all RESs.

- One of the strengths of PIML is its ability to elucidate the behavior of RESs that are costly or infeasible to access directly due to complex environments or technical challenges. For example, in fault detection for RESs such as geothermal energy or ocean current energy conversion, where component access is limited and expensive, PIML offers a significant advantage.
- Another significant merit of PIML in RESs is its improved transparency compared to the black-box nature of classic ML. This not only enables better understanding and interpretation of the developed model and its relation to system behavior but also helps to avoid conventional problems in traditional ML approaches such as overfitting and underfitting.
- One of the main drawbacks in the application of PIML across various RESs is its limited capability to solve complex problems that lack well-established physical laws. For instance, implementing PIML to model ocean current energy conversion requires coupling nonlinear hydrodynamics, wave dynamics, and structural interactions, which are poorly handled by current PIML frameworks. Another example is geothermal energy, where subsurface heterogeneity, multiphase flow, and chemical reactions represent physics that are not fully understood or are too complex to encode in the form of PDEs.
- Another drawback of PIML is that many RESs involve highly nonlinear physics (e.g., multiphase biomass reactions, ocean current dynamics) that cannot be fully captured by existing models. Embedding simplified physics may also bias predictions. Thus, it is important to recognize that reliance on physical laws, until PIML achieves scientific maturity, could be considered its Achilles' heel, particularly for RES problems with strongly nonlinear characteristics.
- Another drawback of current PIML knowledge is its limited applicability to hybrid RESs, as solving these systems requires coupling multiple PDEs (e.g., thermo-hydro-mechanical-chemical in geothermal, aero-structural in wind) simultaneously, which is difficult to implement in existing PIML frameworks.
- Another limitation of PIML compared with classic ML models and various optimization approaches is the scarcity of validation, design, and optimization studies based on field experiments and operational RESs. The current state-of-the-art still relies heavily on theoretical studies.
- Another restriction of PIML in RESs is the limited availability of commercial (or open-source) packages and tools, such as NeuralPDE by Julia [83], for practical implementation of the approach. Considering this, along with the limited validation using field data, it should be emphasized that these limitations arise from the early-stage nature of PIML development. Therefore, many of these issues are expected to be alleviated as PIML advances and matures, not only in RESs but also in other disciplines.
- Integrating sensitivity analysis into problems solved by PIML is a very new an interesting direction [107], as it provides a clear understanding on the contribution of influential factors on the specific parameter evaluated/measured/optimized. It is highly recommended to adopt this strategy in future PIML methods.
- Another interesting approach in novel PIML methods is adopting variable weight of loss functions [92], that effectively extracts the loss of each component based on their contribution which was in contrast of previously accepted method that designated the same weight to all components equally reducing the accuracy of the model.
- Developing scalable PIML models which are capable of operating across varying environmental conditions and system configurations is another interesting approach for future research. For instance, models that generalize across different wind turbine designs, solar farm layouts or real-time integration of PIML with control systems for adaptive optimization, while leveraging Internet of Things (IoT) sensors for continuous learning and decision-making.
- Considering the multidisciplinary nature of implementing PIML in RESs, collaborations between experts in RESs, data scientists, and computational physicists could address complex challenges, such as multi-scale modeling. For instance, integrating chemical and geological phenomena into geothermal systems or combination of PIML with computational material design to fabricate high performance solar cells could be achieved through merging the above-mentioned disciplines.

8. Conclusion

Development of renewable energy systems in the coming years is a global task on the shoulder of the scientific community across all disciplines to protect our blue planet. In the last decade ambitious plans and strategies have been proposed toward transition of 100 % RESs [160–163], however, RESs have always faced with several common obstacles such as lower efficiency, higher cost of product compared to conventional methods, stability, hurdles in large-scale installation, etc. among others. PIML is a novel approach which almost presented 6 years ago, thus, applying its methods in renewable energy systems is quite new, maybe less than 5 years. Indeed, the high potential of PIML makes it one of the hot topics in different disciplines including RESs. By leveraging the PIML approach, many above-mentioned obstacles can be addressed effectively. It is important to note that due to the multidisciplinary nature of RESs and PIML methods, tight collaboration between data scientists and renewable energy experts is essential. It can be anticipated that the PIML approach will further boost the performance of several well-established technologies, such as wind energy, while opening new avenues for emerging renewable energy systems, such as ocean current energy conversion.

CRediT authorship contribution statement

Seyed Masoud Parsa: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparing the first revision of this work, the author used Chat-GPT Vesrion4 to polish the language of manuscript and improving readability. All changes by the AI were reviewed and edited by the author accordingly.

Declaration of competing interest

The author declare there is no conflict of interest.

Data availability

No data was used for the research described in the article.

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