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Towards Physics-Informed Machine Learning-Based Predictive Maintenance for Power Converters – A Review

Youssef Fassi, Vincent Heiries, Jerome Boutet, Sebastien Boisseau, *Member, IEEE*

Abstract— Predictive maintenance for power electronic converters has emerged as a critical area of research and development. With the rapid advancements in deep learning techniques, new possibilities have emerged for enhancing the performance and reliability of power converters. However, addressing challenges related to data resources, physical consistency, and generalizability has become crucial in achieving optimal strategies. This comprehensive review article presents an insightful overview of the recent advancements in the field of predictive maintenance for power converters. It explores three paradigms: model-based approaches, data-driven techniques, and the emerging concept of physics-informed machine learning (PIML). By leveraging the integration of physical knowledge into machine learning architectures, PIML holds great promise for overcoming the aforementioned concerns. Drawing upon the current state-of-art, this review identifies common trends, practical challenges, and significant research opportunities in the domain of predictive maintenance for power converters. The analysis covers a broad spectrum of approaches used for parameter identification, feature engineering, fault detection, and remaining useful life estimation (RUL). This article not only provides a comprehensive survey of recent methodologies but also highlights future trends, serving as a resource for researchers and practitioners involved in the development of predictive maintenance strategies for power converters.

Index Terms—Physics-informed machine learning, predictive maintenance, Power converters, anomaly detection, condition monitoring, fault analysis, remaining useful life, AI, digital twin, power electronics

NOMENCLATURE

AC	Alternating Current	ESR	Equivalent Series Resistance
AI	Artificial Intelligence	FEM	Finite Element Modeling
ANN	Artificial Neural Network	FNN	Feedforward Neural Network
BPNN	Back Propagation Neural Network	GaN	Gallium nitride
CAM	Channel Attention Module	GAN	Generative Adversarial Networks
CNN	Convolutional Neural Network	GMM	Gaussian Mixture Model
CS	Compressed sensing	GP	Genetic Programming
DC	Direct current	GPR	Gaussian Process Regression
DNN	Deep Neural Network	IGBT	Insulated-Gate Bipolar Transistor
DT	Decision Tree	kNN	k-Nearest Neighbors
DWT	Discrete Wavelet Transform	LSTM	Long-Short Term Memory
ESD	Electrostatic Discharge	MD	Mahalanobis Distance
		ML	Machine Learning
		MLCC	Multilayer Ceramic Capacitor
		MLE	Maximum Likelihood Estimator
		MOSFET	Metal-Oxide-Semiconductor Field-Effect Transistor
		NN	Neural Network
		ODE	Ordinary Differential Equation
		PAF	Physical Activation Function
		PCA	Principal Component Analysis
		PCB	Printed circuit board
		PDE	Partial Differential Equation
		PIML	Physics-Informed Machine Learning
		PINN	Physics-Informed Neural Network
		PSO	Particle Swarm Optimization
		ReLU	Rectified Linear Unit
		RF	Random Forest
		RNN	Recurrent Neural Network
		RUL	Remaining Useful Life
		RVM	Relevance Vector Machine
		Si	Silicon
		SiC	Silicon Carbide
		SOM	Self-Organizing map
		SVM	Support Vector Machines

I. INTRODUCTION

From electric vehicles to renewable energy systems, power converters serve as a vital element of numerous electronic systems, and their significance is paramount in diverse fields such as electric mobility, renewable energy generation, data centers, and smart grid systems.

The ever-increasing demand for efficient and reliable power converters in various industrial applications has led to a surge of interest in predictive maintenance techniques. As power converters play a vital role in transforming electrical energy from one form to another, their failure can have significant consequences, including production downtime, financial losses, and even safety hazards.

Despite the elaborate consideration of reliability characteristics in design and control [1], power converter systems face various risks due to complex and severe working conditions. Therefore, ensuring the reliability and safety of power electronic converters is crucial for field applications, especially in safety-critical settings. To this end, preventive activities such as condition monitoring, anomaly detection, fault diagnosis, and remaining useful life (RUL) prediction can effectively ensure that the intended functions are performed reliably and accurately over the operational lifetime of the system. This monitoring of the state of assets also means that components can be replaced at precisely the right moment, neither too early nor too late, reducing wasteful resource expenditure caused by excessive maintenance resources or underutilization, not only to optimize costs but also to lower the related carbon footprint.

Predictive maintenance can be achieved using a combination of model-based and data-driven approaches. Model-based approaches provide insights into the degradation mechanisms of power converter components relying on the physics-of-failure and can be used to simulate the behavior of the system under different operating conditions. However, physical models can be complex and computationally expensive, often rely on assumptions, and may not capture all the degradation mechanisms.

Observational data emerges as a promising avenue to complement physical models. With the potential for over a trillion sensors [2], an abundance of multi-fidelity observations was meant to play a pivotal role in bridging the gap between physics-based models and empirical reality. But, despite the abundance, speed, and variety of available data streams, integrating such multi-fidelity data into existing physical models remained challenging in many real-world cases [3].

This is where machine learning has become widely recognized as a powerful tool for solving complex problems thanks to its ability to process and extract valuable correlations from the massive amounts of data. However, machine learning approaches, although more effective in a supervised mode, often face a significant challenge due to the scarcity of labeled data, limiting their practical applicability and hindering their performance in real-world scenarios. Additionally, traditional machine learning approaches are ill-equipped to extract interpretable insights and knowledge from this abundance of data [4] and often lack the incorporation of physical constraints

and laws, leading to less accurate and reliable predictions.

Physics-informed machine learning (PIML) addresses this issue by incorporating prior physical knowledge into the learning process. Although recently introduced, this new paradigm has been investigated and explored in a number of fields, including fluid mechanics [5], chemistry [6], geology [7], power systems, and several review papers have explored different aspects of PIML in various domains. For example, Karniadakis [3] highlighted key trends in embedding physics into machine learning, addressing capabilities and limitations, and showcasing PIML applications. Von Rueden [10] introduced a taxonomy and classification framework based on knowledge integration into the ML pipeline. Rai and Sahu [11] reviewed methods fusing physics-based and ML models in cyber-physical systems, introducing metrics for hybrid model evaluation. The review by Sansana [12] explored hybrid modeling techniques, emphasizing data-driven and white-box models in chemical and biochemical applications. Willard [13] discussed the integration of traditional physics-based modeling approaches with machine learning to improve engineering and environmental system modeling. Meng et al. [14] surveyed PIML in simulation models and surrogate modeling, emphasizing physics knowledge and integration methods. Bradley et al. [15] highlighted the advantages of combining first-principles and data-driven methods, assessing hybrid modeling, PIML, and model calibration. Huang et Wang [8] delved into Physics-Informed Neural Networks (PINNs) in power systems, covering paradigms like state estimation, anomaly detection, and power flow calculation. Xu et al. [16] reviewed PIML methods in reliability and system safety applications, focusing on knowledge aggregation and integration methods. Rizvi et al. [17] presented a state-of-the-art review of PIML applications in Structural Health Monitoring, addressing challenges related to noisy datasets, dimension reduction, and enhanced structural reliability.

As for the predictive maintenance of power converters, burgeoning studies have taken place with surely more potential to explore, as it is now to expect a reduction in the learning burden for the algorithm. This stems from the fact that the introduction of prior knowledge already accounts for certain behaviors and helps constrain the search space, thereby reducing the reliance on large amounts of data. This also allows for better generalization of the solution because the physical equations describing the underlying physical phenomena are based on generalizable knowledge.

This review article aims to provide an overview of the current state of the art in predictive maintenance of power converters. The article will cover various aspects of predictive maintenance, including the degradation mechanisms of power converter components, model-based approaches, data-driven approaches, and the process of condition monitoring, parameter identification, feature extraction, failure detection and diagnosis, introducing some of the recent and novel techniques in the field. The article will provide valuable insights into the current research trends and future directions in this field and will help researchers and practitioners develop effective predictive maintenance strategies for power converters. The

remainder of this review is organized as follows. Section II introduces the degradation mechanisms of the main components of power converters. Section III discusses the model-based approach used in predictive maintenance, while Section IV focuses on data-driven solutions for condition monitoring, fault diagnosis, and RUL estimation. Section V exhibits the PIML paradigm and presents cutting-edge development for predictive maintenance. Section VI presents the concluding remarks.

II. DEGRADATION MECHANISMS

Power converters are vital components in many electrical systems, and they come in all kinds of topologies to cater to different needs and applications, whether they be inverters, rectifiers, DC-DC converters, or others [18], [19]. These converters are composed of both passive and active power devices, some of which are more susceptible to failure than others [20], [21]. The literature indicates that capacitors and semiconductors, are among the most critical components in the event of failure. Additionally, PCBs (Printed Circuit Boards) have also been identified as key components that can significantly impact system performance and reliability [22] (**Fig. 1 (a)**), as they are subject to various operational and environmental stresses that can lead to degradation and failure in a composite manner [23]. Temperature, vibration, and humidity are among the factors that significantly influence the performance and lifespan of electronic components, with temperature alone accounting for around 55% of causes [23], [24] (**Fig. 1 (b)**). By understanding the underlying physics of degradation, one can discern the key features of the degradation mechanism and how it affects the main components of modern power converters [25]. This section focuses on the main degradation mechanisms, their combinations, and their impact on power converter components.

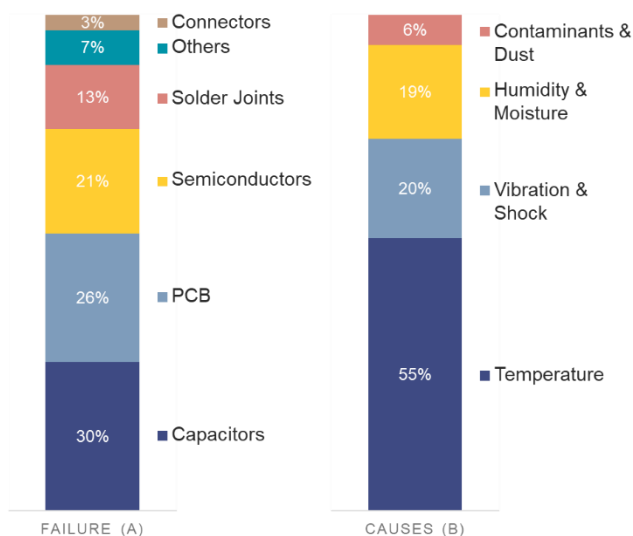


Fig. 1. Failures impacts (a) and associated causes (b) in power electronic systems

A. Power semiconductors

Semiconductor devices play a crucial role in power converters. In the form of switches, rectifiers, overvoltage regulators, they control the electrical energy as required by the power conversion process. There are several types of power semiconductors that are used in power converters, including diodes, thyristors, MOSFETs, and IGBTs, each selected based on factors like voltage and current ratings, frequency range, and controllability.

Power semiconductors fall into three categories: non-controllable switches, semi-controllable switches, and fully controllable switches. Non-controllable switches, exemplified by power diodes, operate solely based on circuit conditions. Semi-controllable switches, on the other hand, can be externally controlled but lack modulation in the on-state current. Fully controllable switches, such as MOSFETs, BJTs, and IGBTs, enable precise control over switching and output parameters, both activated and turned off [20], [21].

Semiconductor devices are susceptible to failures due to various environmental stresses like high temperatures, humidity, high voltages, and current loads, either from inherent factors within the die structure or external package-related issues [23], [26], [27], [28], [29], [30]. Thermal-induced failure, notably thermal runaway, stands out as a common and challenging issue to predict. Thermal runaway arises when a device's temperature increases, subsequently elevating its electrical resistance, causing more current to flow, and ultimately culminating in device failure [23], [26], [27], [30].

Furthermore, short circuits emerge as another prevalent source of failure, capable of affecting neighboring switching devices [31]. Short circuits may result from sudden or gradual degradation processes [32]. In the context of GaN-based semiconductors, short-circuit failures can materialize within sub- μ s under different failure modes [33], [34]. SiC-based semiconductors, while having higher temperature resistance than their Si counterparts, are more susceptible to short circuit failures due to their lower reverse breakdown voltage [35], [36]. These devices are also vulnerable in the gate-source structure [37], [38], [39].

Moreover, Electrostatic discharge (ESD) is a common cause of failure for power electronics systems, accounting for 17% of field return failure causes [40]. This risk is especially pertinent in high-voltage environments, where the rapid flow of charge leads to high currents and voltages between system components. ESD-induced damage manifests through thermal failure, junction damage, and gate oxide breakdown [45]. Bipolar transistors, MOSFETs, and diodes can all succumb to ESD events, characterized by high currents causing leakage or shorting of junctions [41], [42], [43]. These failures are often linked to gate oxide breakdown and junction thermal failure at high electric fields [44].

Additionally, humidity and moisture can contribute to semiconductor failures, especially in high-temperature environments. Moisture infiltration through non-conductive

packaging materials can lead to deformations, affecting the device's reliability. Thermal load also plays a role in packaging failures at different critical sites, among which baseplate solder joints, chip solder joints, and wire bonds [31], [45], [46], [47]. Packaging-level failures can range from open circuit hard failures to bond wire attach failures [48].

The diverse range of semiconductor materials, such as Si, GaN, and SiC, introduces various failure mechanisms associated with thermal stress, short circuits, and ESD [45], [46], [49], [50], [51], [52], [53]. These failures can affect components at both the device and packaging levels.

B. Capacitors

In the domain of power electronics, capacitors play a crucial role in a range of applications, such as energy storage, ripple voltage filtering, and power factor correction, to name a few [54]. The working principle of aligning dipoles inside a dielectric allows them to store energy in an electric field. An ideal capacitor stores energy with no resistance, but real capacitors have non-idealities (**Fig. 3**), including resistances ESR (Equivalent Series Resistance) and $R_{leakage}$, spurious capacitances, and inductances ESL (Equivalent Series Inductance) [55], [56].

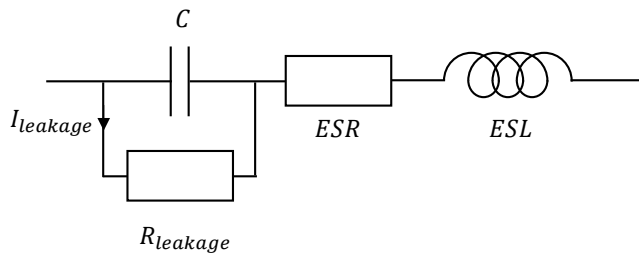


Fig. 3. Common equivalent capacitor model of a real capacitor (other models with various accuracy to be found in [57], [58])

Power converters utilize different capacitor types, primarily electrolytic, film, and ceramic capacitors [59] (**Fig. 4**). Each type has distinct topologies and underlying principles, requiring a grasp of their fundamental traits, especially regarding potential issues and failures.

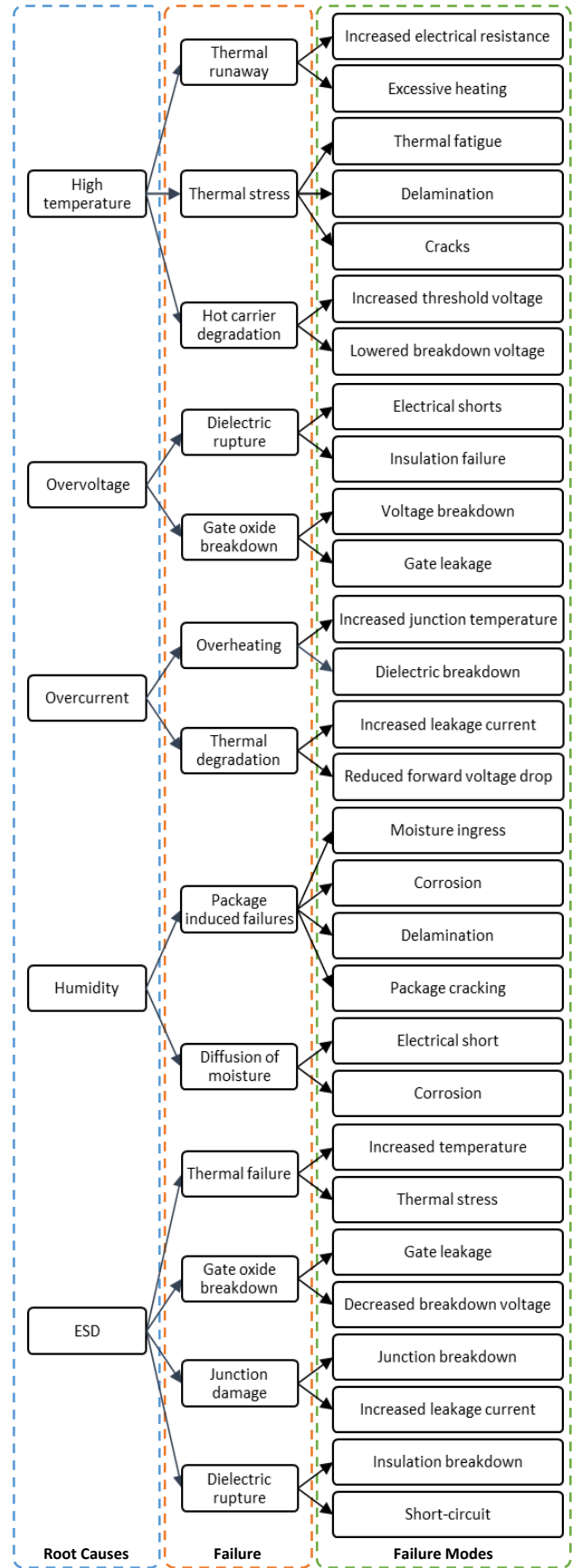


Fig. 2. Main failure causes, mechanisms and modes in power semiconductors

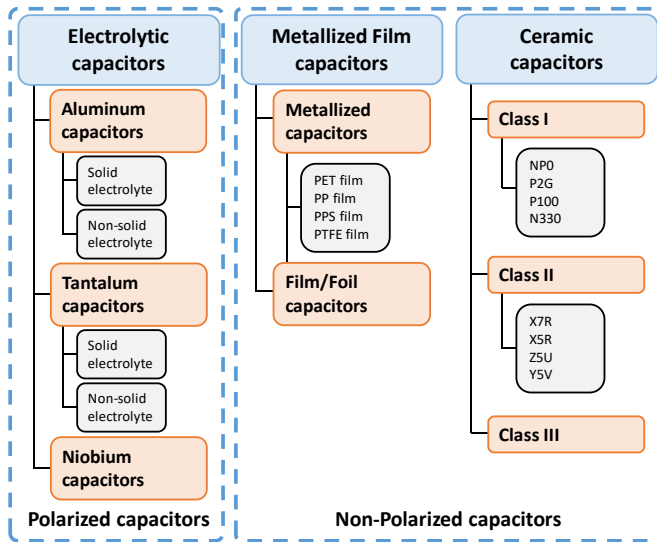


Fig. 4. Common capacitors used in power electronic converters

Capacitors are influenced by stress factors such as temperature, voltage, ripple current, charge-discharge, and humidity. Monitoring the degradation and assessing the health of capacitors require the measurement of parameters such as capacitance, ESR, dissipation factor, and insulation resistance. Consequently, researchers have dedicated significant efforts to developing data-driven and statistical models to effectively evaluate the state of capacitors, estimate their reliability, and predict their RUL [60].

With acknowledging the importance of capacitors in power electronics systems and the challenges in predicting their failures, extensive research has been conducted to understand failure mechanisms, develop methods for lifetime prediction, and enhance reliability design and condition monitoring [61]. However, current methods have limitations in reflecting changes in capacitor state during service and predicting sudden failures.

1) Electrolytic capacitors

Electrolytic capacitors are used for electrical energy storage and are renowned for voltage ripple smoothing. They are made of a solid or non-solid electrolyte layer that serves as the cathode and an anode foil that has a thin oxide layer and acts as a dielectric [62], [63] (**Fig. 5**). They are cost-effective and offer high capacitance, but are susceptible to wear-out and catastrophic failures due to electrical and thermal stress [60].

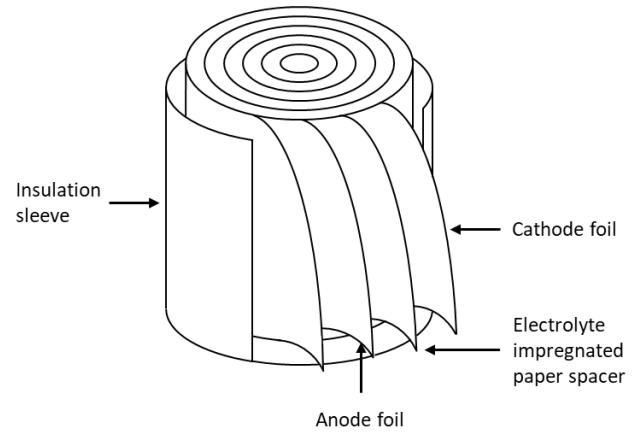


Fig. 5. Topology of an aluminum electrolytic capacitor

Industry standards define an electrolytic capacitor's end-of-life as a 10% capacitance loss and a 250% increase in ESR under thermal stress or a 20% decrease in capacitance rating and a 280-300% ESR increase due to electrical stress [60], [64], [65].

Thermal overstress can lead to electrolyte loss through evaporation, accelerated by high temperatures and ripple currents [60], [66], [67], leading to capacitance loss and ESR increase. Dielectric imperfections generate leakage currents during charging, causing evaporation pressure and speeding wear-out. Pulsed charges and overvoltage further contribute to performance decline [68], [69].

In solid electrolytes, thermal overstress can degrade the conductive polymer or create defects, affecting conductivity [70], [71]. Electrical overstress can cause dielectric breakdown, resulting in a short circuit or ignition, particularly in solid MnO_2 tantalum and niobium capacitors [62], [72].

Loss of electrolyte is the main cause of degradation in electrolytic capacitors, and thermal stress is a contributing factor [68]. Factors like ripple current, voltage, and vibration also affect their lifespan. Interested readers can refer to [73] for a comprehensive review of electrolytic capacitor failure modes and related causes.

2) Metallized film capacitors

Metallized film capacitors feature a metallic coating on polymer dielectric films [74], with electrodes typically made of aluminum and zinc in pure or alloyed forms [60] (**Fig. 6**). Common dielectric materials include polypropylene (PP) and polyethylene terephthalate (PET) [75].

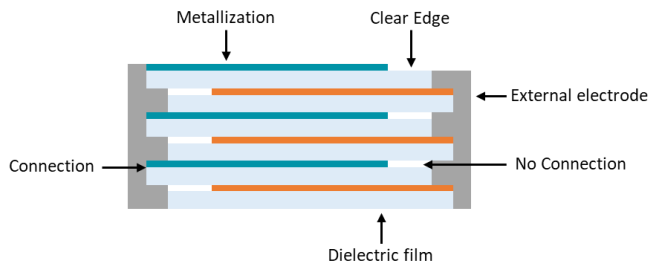


Fig. 6. Topology of a layered metallized film capacitor

PET has a higher capacitance and higher operating temperature compared to PP, which is in turn preferred for high voltage applications and moisture resistance [76]. However, thermal aging causes the deterioration of PP electrodes and thus increases the loss factor [77].

Metallized film capacitors are notable for self-healing, leveraging inherent dielectric defects [60], [78]. It consists of localized heating causing the metallization layer to evaporate and isolate the defect region, preventing short circuits [78], [79]. This leads to incremental soft failures that, when accumulated, ultimately result in catastrophic failure.

Self-healing is significantly influenced by voltage level, interfacial pressure, and metallization resistance [76], [78]. Specifically, increased voltage level is accountable for capacitance loss and ESR increase [80]. It can also extend the healing time, leading to catastrophic failures.

High operating power levels raise the dielectric temperature, particularly for polymers with low phase transition temperatures, causing thermomechanical and volumetric changes [60], [75]. Additionally, increased temperature decreases the voltage breakdown of capacitors, especially the PP-based ones, making catastrophic failures more likely.

Pulsed power applications further introduce stresses, combining degradation mechanisms and elevating failure risks [81], [82]. Peak and AC voltages, thermal aging, and humidity are prominent stressors. Humid environments can result in corrosion, disrupting current distribution, causing localized heating, and ultimately leading to failure [60], [75]. For readers seeking a synthetic description of failure causes, modes and effects of metallized film capacitors, we recommend consulting the reference in [76].

3) Ceramic capacitors

Ceramic capacitors are the most commonly used capacitors in modern power electronics. They are used in resonant circuits and filters and are also used extensively in high-temperature and high-frequency applications [83]. Driven by increasing demand from the automotive industry due to the development of electric vehicles, as well as the increasing adoption of 5G technology in the telecommunications sector, the utilization of ceramic capacitors has witnessed significant advancements [84].

Ceramic capacitors are known in the form of multilayer ceramic capacitors (MLCCs) which are the most commonly used type of ceramic capacitor (**Fig. 7**), characterized by high capacitance and compactness, and are widely used in modern day electronics [85], [86]. MLCCs consist of a series of ceramic layers interleaved with metallic electrodes.

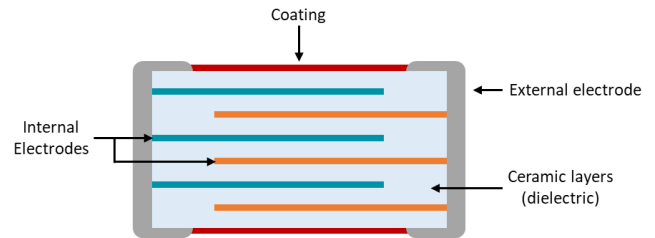


Fig. 7. Topology of a multilayer ceramic capacitor

Ceramic dielectrics in capacitors fall into three classes; Classes I and II are prominent. Class I dielectrics, composed of paraelectric materials [83], [87], offer stability under various conditions making them suitable for resonant circuits. Industry-specific codes like COG (NP0) and P2G apply. In contrast, Class II dielectrics, using ferroelectric ceramics [88], are common in power electronics, known by codes like X7R and X5R.

As for the metallic electrodes, they were primarily made of precious metals like silver and palladium alloys, ideal for sensitive applications [89], [90]. To reduce costs, base metal electrodes (BME), typically nickel (Ni), became standard. However, BME manufacturing introduced oxygen vacancies in ceramic layers, causing parametric reliability concerns [90], [91]. These vacancies boost conductivity, lowering insulation resistance (IR), and leading to operational failures.

Further, under high voltage stress, oxygen vacancies act as electron traps, giving rise to positively charged electron holes [90], [92]. This phenomenon sets off chain reactions leading to catastrophic breakdown that may result in issues like ceramic melting, short formation, or mechanical delamination and cracking [59].

MLCCs are vulnerable to humid environments, particularly for the widely used class II BaTiO₃-based dielectrics [92], [93]. The presence of moisture initiates electrolysis, generating protons that increase leakage current and reduce capacitance [94]. MLCCs are also vulnerable to ESD, leading to permanent parameter shifts like capacitance and insulation resistance [95].

C. Printed circuit board (PCB):

PCBs serve as foundational mounting components in modern electronic devices. They come in various forms, differing in layer count, electrical connections, and cooling systems [96]. PCBs are typically made of a non-conductive material, such as fiberglass-reinforced epoxy, with conductive traces for circuit connections. The specifics of the materials are usually a trade-off between the desired performance and the manufacturing process [97]. PCBs used in power electronic converters can be

susceptible to various degradation mechanisms, including mechanical failure due to vibration, thermal cycling, and environmental stressors [98], [99].

Due to different material choices with different coefficients of thermal expansion, thermomechanical strain appears, which can cause solder joint failures and delamination of the PCB layers [100], [101]. Further, vibration and thermal cycling cause oxidation, fretting corrosion, and contact force decrease on the connector side, leading to power loss of the converter [102], [103].

ESD and moisture ingress are additional PCB degradation factors. ESD results from electrical charge accumulation, potentially damaging components [104], [105], [106]. Moisture can infiltrate PCBs, accelerating degradation by causing delamination and affecting switching frequency [107], [108]. Understanding these PCB degradation mechanisms is the foundation for implementing predictive maintenance strategies to ensure the reliability and extend the lifetime of the board [109].

III. ANALYTICAL MODELING

The quest for predictive maintenance in power converters has led to the development of various modeling approaches for degradation assessment and failure prediction. These approaches aim to provide valuable insights into the health and performance of power components. While the primary focus is predictive maintenance, it is essential to recognize that the journey towards accurate predictions has evolved through different stages.

A. Empirical and semi-empirical modeling

Empirical modeling was an initial step towards estimating the degradation and failure of power converters. Early approaches, such as MIL-HDBK-217F, FIDES, and Telcordia, mainly used data-driven models based on statistical curve fitting of historical failure data [110], [111]. These handbooks were originally developed for the defense and telecommunications sectors, where they captured the influence of various stressors on component failure rates. For instance, a capacitor's failure rate was expressed as a product of temperature stress (π_T), voltage stress (π_V), environmental stress (π_E), quality factor (π_Q), and capacitance factor (π_C) as in (1):

$$\lambda_{cap} = \lambda_b \pi_T \pi_V \pi_E \pi_Q \pi_C \quad (1)$$

As these models were developed, they did not always consider the specific requirements of power components, let alone power systems. As technology evolved, it became evident that a more adaptable and comprehensive approach was needed. This led to the emergence of semi-empirical modeling, which blends empirical data with a basic understanding of the physical mechanisms underlying failures.

The most widely known model is surely the Coffin-Manson model, which describes the number of cycles to failure N_f of an

IGBT as inversely proportional to the junction temperature fluctuation ΔT_j :

$$N_f = A \times (\Delta T_j)^{-\alpha} \quad (2)$$

where A and α are curve fitting parameters [112]. A further detailed empirical model accounts for bond wire lift-off and baseplate solder fatigue, as given by [111], [112], [113], [114]. For capacitors, lifetime estimation L depends on various factors including temperature, current, voltage, frequency, and environmental conditions [68]. Similarly, a Coffin-Manson equation is utilized as a lifetime model for PCBs in a drop test setting [115]. Thermal cycling and vibration modeling lifetime models are also given in [101]. While semi-empirical models are useful for making detailed predictions about specific component performance, they may fall short by lacking the inherent physical structure of power devices and the underlying failure mechanisms. In contrast, model-based approaches have gained popularity by utilizing mathematical models that simulate the underlying physics and mechanics of a system (Fig. 8). By incorporating more detailed information, these approaches offer more accurate predictions of system performance under varying operating conditions.

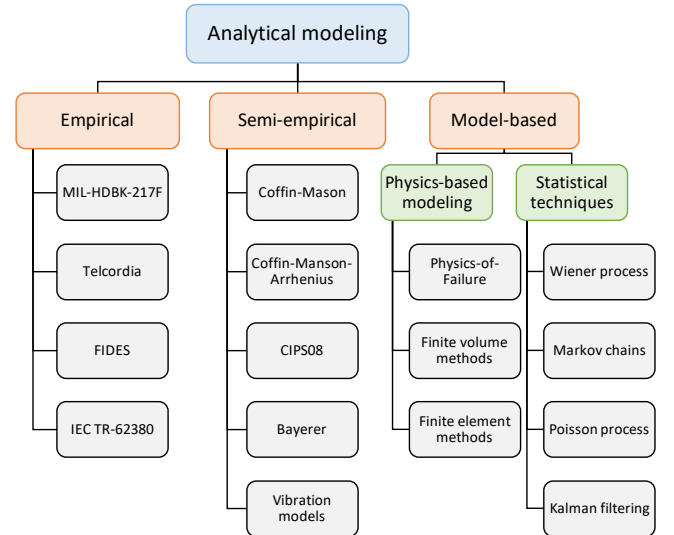


Fig. 8. Analytical modeling for lifetime assessment of power converters

B. Physics-based modeling

Utilizing the physics-of-failure approach and advancements in computational methods, physics-based modeling offers an alternative to empirical models. Unlike empirical models, physics-of-failure models require a thorough understanding of the failure mechanisms of power devices, enabling the modeling of stresses within power module assemblies. Statistical techniques, such as Wiener process [116], Poisson process [117], Markov chains [118], and Kalman filtering, are then applied to directly link this information to reliability, allowing for more accurate and detailed predictions of performance and failure. These techniques are also leveraged

by the development of white-box dynamic identification methods for different power converter topologies [119], [120].

For example, a reliability model for metallized film capacitors has been developed in [121] based on degradation mechanisms. The model considers two capacitance loss dynamics - a gradual continuous one induced by dielectric film aging and a discrete loss due to random self-healing under temperature and voltage stresses. The aging process of the dielectric film is characterized using the Wiener process, where the aging rate is temperature-dependent. The random self-healing events are captured through a Poisson process, where the rate parameter of the process is related to the operating voltage and the dielectric film aging rate.

In another study [122], a model-driven method combines both theoretical models and optimization techniques to estimate the state of health and predict the RUL of electrolytic capacitors using both the unscented Kalman filter and particle filter frameworks for tracking degradation and improving prediction accuracy.

Numerical simulation methods like finite element analysis and finite volume analysis are developed to model the electrical and thermal properties of power components and the influence of neighboring components on their thermal degradation [57], [123], [124], or to model temperature distribution and evaluate critical temperature fields for PCBs [125], [126].

The study in [127] employs a model-based approach for forecasting the RUL of a DC-DC converter, which uses interval model-based prognostic techniques based on polytopes and particularly zonotopes with Extended Kalman Filter. Zonotopes are geometrical objects [128] used, in this context, to represent parameter uncertainty over time and define trusted regions of parameter space.

In [129], a comprehensive lifetime evaluation of three-level inverters is conducted. This evaluation considers factors like dc-link voltage stress, switching frequencies, and mission profiles. It begins by modeling component lifetimes using Weibull distributions and then conducts system-level reliability assessment using reliability block diagrams and Monte Carlo simulations.

IV. DATA-DRIVEN MODELS

While physics-based models are often used to describe system behavior theoretically, they can be limited in scope due to their

inability to account for unknown noises, nonlinearities, and unseen dynamics that often arise as lumped modeling errors. These models may fail at accurately describing real-world observations, leading to significant discrepancies between their predictions and actual measurements [130]. This is particularly critical in power converter maintenance, where accurate and reliable predictions are vital.

To this end, data-based methods have gained popularity in recent years, leveraging large amounts of data from sensors and other sources to predict equipment failures and schedule maintenance before an outage occurs [131]. The quality of the collected data is crucial to the accuracy and reliability of the predictive maintenance workflow that is presented in **Fig. 9**. The data collection phase includes information from installed sensors and off-board sources like historical records, fleet-wide data, or even data obtained from virtual sensors. Once the data is collected, it undergoes some preprocessing, such as cleaning and normalizing, to ensure its quality and suitability for analysis.

The processed data then feeds into the predictive maintenance model at the core of the framework, which operates in a cyclical manner and is detailed in the following subsections. When the model requires refinement or improvement, the data collected from the sensors and off-board sources is used to update and train the model, creating a continuous loop of learning and enhancement. Once the model has reached a satisfactory state, it transitions into the inference block, which assesses if maintenance is needed based on analysis results. Interventions, if deemed necessary, may involve adjusting power converter operating parameters to extend its lifespan. This proactive approach aligns with economic and logistical considerations, enhancing efficiency and longevity.

The maintenance planning phase eventually loops back to the data collection stage, with the consideration of the new state of the equipment that has undergone maintenance. This cyclic nature of the data-driven framework ensures an ongoing and iterative process where data is continually collected, analyzed, and utilized to improve predictive maintenance strategies. By integrating model training and inference, this framework offers a comprehensive approach to maximize equipment reliability, minimize downtime, and optimize maintenance operations.

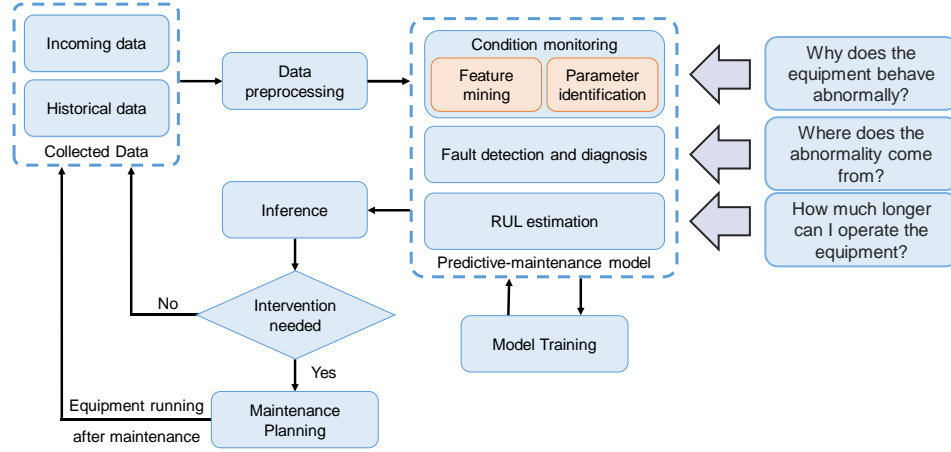


Fig. 9. Predictive maintenance workflow

We can identify that the predictive maintenance model relies on key data-based methods used for power systems: condition monitoring, fault detection and diagnosis, and RUL estimation.

A. Condition monitoring

Condition monitoring in power electronics is a multifaceted process that entails identifying system parameters and extracting features. These tasks can be done sequentially, starting with feature extraction, or separately. The insights derived from condition monitoring serve as a foundation for fault detection and prognosis, providing valuable information [132].

1) Parameter identification

Identifying parameters in power electronic systems is challenging due to instrumentation constraints, high switching frequencies, and small variations in parameters over time. Non-invasive methods, which estimate the parameters indirectly from physical signals, are highly valued for their cost-efficiency and sensorless condition monitoring.

In recent years, optimization methods, aided by AI, have become dominant for parameter identification. These methods offer advantages in handling disturbances, assessing uncertainty, and adapting to system changes, enabling effective power electronic systems' maintenance and control [130].

Rojas-Dueñas et al. [133] employ nonlinear least squares optimization to identify power converter parameters, parasitic effects, and control loop characteristics. The method is applied to various commercially available DC-DC converter topologies using only input and output terminal data, collected during steady-state and transient conditions. The novelty lies in its precise online parameter identification for power converters.

Machine learning models are prominent as well in the parameter identification area. The work in [134] uses an artificial neural network (ANN) model to estimate the output current ripple in an AC-DC interleaved boost converter

considering factors such as inductance current ripple, switching frequency, and load changes. The developed ANN model outperforms alternative approaches such as linear regression (LR) and random forest (RF) in terms of accuracy. In [135], a deep learning approach is proposed for the adaptive steady-state modeling of a resonant DC-DC converter. The deep learning method provides precise voltage gain across a wide range of switching frequencies and loading conditions, overcoming modeling problems associated with other techniques. Finally, an ANN-based method is proposed in [136] for identifying the impedance model of voltage source inverters under a range of operating points, allowing efficient impedance estimation.

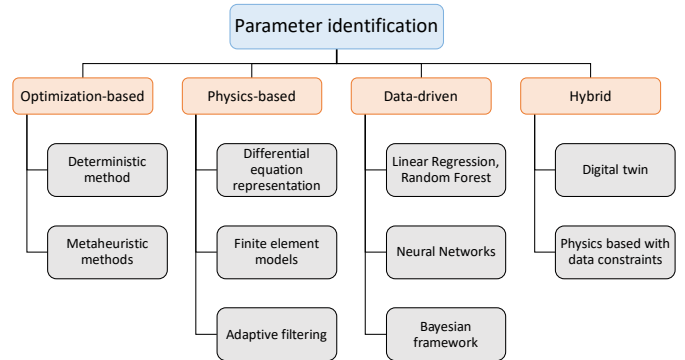


Fig. 10. Overview of parameter identification methods for power converter applications

2) Feature mining

Feature mining steps are critical in refining raw data for optimal performance in applications such as fault diagnosis. Feature mining involves exploring the structure of the dataset, which includes classical data processing, discovering groups of similar data points through data clustering, identifying data distribution through density estimation, reducing the number of features through data compression, and integrating multiple

sources of information through data fusion [137]. More feature engineering work is retraced in **Table 2**.

For example, in a single-phase cascaded multilevel inverter system [138], a feature mining strategy utilizes a Fast-Fourier transform on voltage signals to extract the frequency responses, with added phase information, which enhances fault separation. Principal Component Analysis (PCA) [139] is used to extract fault signal features and reduce samples dimensions. In practice, it reconstructs frequency domain data through a linear combination of representative eigenvectors derived from the covariance matrix. This approach retains a user-defined 85% of data variance while achieving over 97% classification accuracy and offering high model sparsity reflected by low inference time.

Wavelet transform analysis is widely used in power converter applications as a signal processing tool for feature extraction [140]. In particular, discrete wavelet transform (DWT) [58], [141], [142], [143], [144], [145], [146], [147], decomposes a signal in a multiscale fashion to separate high and low frequency content. For example, [148] used a three-scale Haar-based DWT to estimate the ESR from capacitor voltage, with improved sensitivity compared to other methods. In [149], a novel deep learning model called WaveletKernelNet (WKN) is introduced, which incorporates a continuous wavelet convolutional (CWConv) layer to replace the first convolutional layer of vanilla CNNs. This CWConv layer learns scale and translation parameters directly from the raw data, enabling the creation of a customized kernel bank specifically tailored to extract defect-related impact components from vibration signals. Experimental results demonstrate that WKNs outperform CNNs by over 10%, highlighting the CWConv layer's role. Additionally, theoretical analysis and feature map visualization further reveal that WKNs offer advantages such as enhanced speed, interpretability, and a reduced parameter count.

In [150], time-domain features are used to map the degradation of IGBTs in inverter-driven motor drives. The approach transformed three-phase inverter current (I_a , I_b , I_c) into two-phase current (I_α , I_β) using Concordia Transformation.

Features like standard deviation, skewness, and kurtosis are extracted, and classification is done using an SVM. An insightful look has been drawn to the localizing capability of the mean current vector, grouping spurious resistance faults into a pattern of operating stages. Experimental results confirm the method's robustness, yielding an average classification accuracy of 94%. Similarly, in [151], the extended park vector approach extracts current and load features for open and short circuit faults in a three-phase two-level inverter. PCA reduces data dimensionality, revealing inconsistencies between healthy and faulty currents.

Self-organizing maps (SOMs) have been used for IGBT health state estimation [152]. This approach clusters IGBT states based on degradation levels, using data from temperature, current, and voltage measurements. Even though SOM has shown its efficiency in this setting, [153] has outlined its pitfalls when it comes to online monitoring, with concerns over data collection and SOM updating.

Besides, multimodal feature extraction methods have been proposed to improve condition monitoring and fault diagnosis accuracy by extracting relevant features from multiple sources. One study applied multi-domain feature extraction for a three-level inverter [144], using time-scale, frequency-energy, and time-domain features from AC line voltage data of various fault types. These features were input to a deep belief network to train a fault diagnosis model. Another study employed a Low-rank Matrix Fusion [154] method to fuse voltage and current signals and used a Sparse Transformer for extracting diagnostic information. Another method uses an improved attention mechanism module that improves the network's ability to learn features and a denoising threshold algorithm for the diagnosis of a dual-active bridge converter [155]. A fourth study formulates a composite failure precursor for SiC MOSFETs using a genetic programming (GP) [156]. Data fusion techniques identify relevant precursors from potential failure precursors and combine them nonlinearly with GP.

A comprehensive look at feature domain extraction in the case of power converters is detailed in **Table 1**.

Table 1. Feature extraction methods and referenced signals used

Feature Domain	Methods	Signals used
Time-domain features	Time domain statistics (mean, skewness, kurtosis, peak-to-peak, etc)	Voltage [144], [157], three-phase current [150], [151], [158], [159], load current [160], temperature [161]
	Multivariate statistics (T ² , Q, SWE)	Three phase currents and voltages, input current and voltage, output voltage [162], [163], [164]
	Variational Mode Decomposition	Current, voltage, temperature, power [165]
	Empirical mode decomposition	Three phase line voltage [144]
		IGBT current, load current, input and diode voltage [143]
		Three phase current measurement [158]

	ResNet with CAM [155],	Non-linear modeling capability, the residual connections prevent gradient problem, attention mechanism adaptively establishes dependency between features, denoising capability
Frequency Domain Features	Fast Fourier Transform	Output voltage measurement [138] Three phase current measurement [158] Output currents and voltages [166]
Time-scale domain features	Discrete Wavelet Transform	Three phase current [141], Electrolytic capacitor ripple current and voltage [58], DC link voltage [142], Inverter terminal voltage [145], [147], Inverter current [146], Electrolytic capacitor terminal voltage [148], multilevel converter five phase current [167]
	Wavelet Packet Decomposition	Diode voltage [143], Three phase line voltage [144]
Cross-domain features	PCA and variants	Three phase current measurement [151], Three phase currents and voltages, input and output voltages, input current [162], [163], [164]
	Park Vector Approach - DQ transformation	Three phase current measurement [151], Output currents and voltages [136], [166]

Table 2. Feature engineering techniques used for power converters

Feature engineering	Method	Ref
Data compression	Principal Component Analysis (PCA)	[138], [143], [151]
	Compressed sensing (CS)	[58]
	Mean Current Vector	[150]
	Generalized Discriminant Analysis	[158]
	Bidirectional gated recurrent unit	[154]
	Wavelet Compression	[168]
	t-SNE	[155], [169]
Data Fusion	Low-rank Matrix Fusion	[154]
	Genetic Programming	[156]
	Ensemble learning	[152], [162], [163]
Generative models	Auto-encoder	[170]
	GAN	[171]

B. Fault detection and diagnosis

Fault detection is a crucial part of predictive maintenance. It identifies deviations from normal behavior, revealing potential performance degradation and impending failures [172]. The power of machine learning-based fault detection lies within the detection of early system changes that indicate ongoing

degradation rather than catastrophic failures, which are best addressed by hardware safety mechanisms [143]. Once an anomaly is detected, fault diagnosis involves a more detailed analysis of the root cause and location of the fault, allowing maintenance teams to take proactive action to prevent costly downtime. The process typically involves performing tasks like classification, regression, or clustering, leveraging relationships learned from training data. **Table 3** summarizes fault detection and diagnosis methods for power converters, considering their practical advantages and limitations.

The choice of fault detection and diagnosis method depends on the type of dataset, whether it is labeled, unlabeled, or partially labeled, and the category of the training algorithm family, which can be categorized into three groups:

1) Supervised methods

When it comes to machine learning, supervised learning is a popular technique that involves training an algorithm on labeled data, where input data is paired with corresponding output labels, and the algorithm learns to map inputs to outputs by analyzing these input-output pairs (**Fig. 11**). A range of techniques are employed in supervised learning, including decision trees (DT), support vector machines (SVM), k-nearest neighbors (kNN), neural networks, and ensemble methods aggregating the output of multiple classifiers such as Random Forests (RF). Supervised learning generally offers superior performance in terms of accuracy and efficiency compared to semi-supervised or unsupervised approaches [141] when labeled data are available, but is challenging for physical systems due to rare event classification.

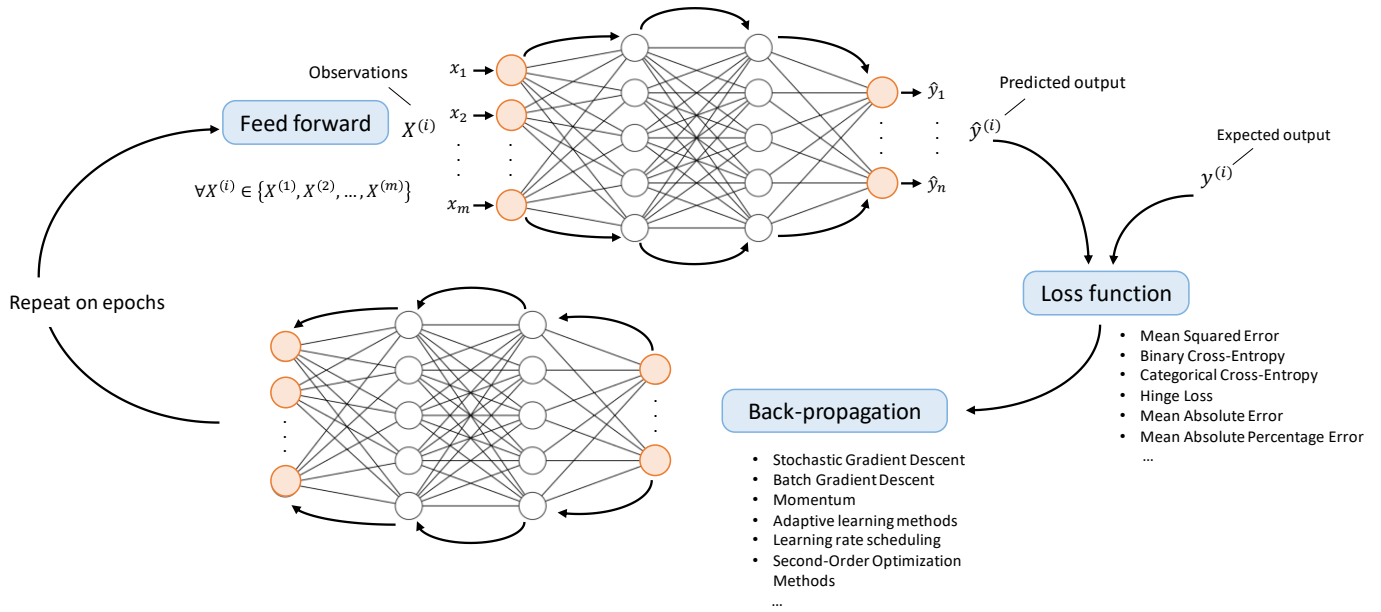


Fig. 11. Supervised learning pipeline

In [168], a deep feed-forward neural network was used to detect open-circuit faults in IGBTs in a phase-shifted full bridge DC-DC converter. The transient features selected from current and voltage measurements were considered to be indicative of faults, such that the neural network achieved an average accuracy of over 97%, outperforming other popular classifiers such as RF, kNN, and SVM.

In [142], SVM classifiers have also proven effective for detecting and classifying individual and simultaneous open circuit faults in power switches, even with substantial measurement errors and relying solely on the DC link voltage signals. A similar study proved the efficiency of SVM exploiting multivariate features [164].

The research in [145] uses an ANN to identify nine distinct faults associated with IGBT and diode wear-out in a single-phase inverter. The algorithm effectively detected and classified faults in both component failure and accelerated degradation scenarios, achieving accuracies of 97.4% and 94.2%, respectively.

The work in [173] presents a fault diagnosis method based on one-dimensional CNNs that has shown promise for fault diagnosis in a two-level three-phase inverter. Faulty classes are identified through voltage measurements, obviating the requirement for additional processing and rendering the data amenable to direct modeling. The model shows a high classification accuracy of over 98% when confronted with different noise levels in 22 identified faulty classes.

Ensemble learning methods, including bagging, boosting, and random sub-space have been combined with classical supervised learning algorithms like kNN, SVM, and DT for fault detection and diagnosis to enhance the predictive power and robustness of the overall model [174]. In one study [162], the objective was to leverage meta-algorithms and ensemble techniques to improve the effectiveness of kNN, SVM, and DT models in identifying and analyzing faults in a power converter-connected PV system. The proposed methods showed superior fault diagnosis performance compared to classical supervised neural network models. Another approach presented in [163] involved an ensemble technique using SVM, DT, and kNN algorithms as baseline classifiers, along with ensemble learning methods. Interval-valued data are utilized to further improve the results when it comes to considering uncertainty, as the data are represented using an interval rather than a single value.

2) Unsupervised methods

Obtaining labeled data can be challenging, and for large sample sizes, impractical, particularly for applications like power converter systems. Unsupervised learning offers a solution by training algorithms on unlabeled input data, effectively extracting valuable information from large datasets (Fig. 12). Some common examples of unsupervised learning include clustering, anomaly detection, and dimensionality reduction using some classical architectures, including autoencoders (AE), restricted Boltzmann machines, and generative adversarial networks (GAN).

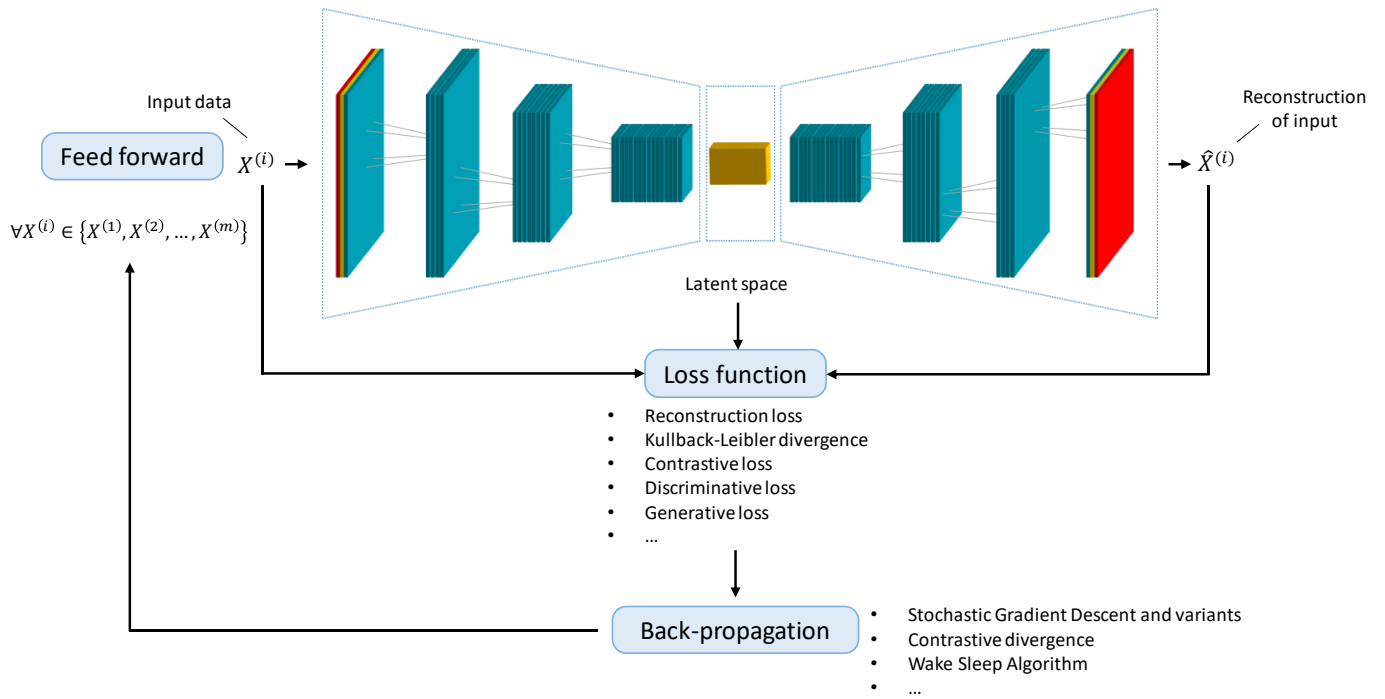


Fig. 12. Unsupervised learning pipeline, example of an autoencoder

In one approach [157], Jiang et al. use unsupervised learning for fast online fault detection and diagnosis of DC-DC converters. The normal output range is estimated based on Gaussian process regression (GPR) [175], and a genetic algorithm calculates extreme values of statistical features. These extreme values represent normal operating ranges, aiding in detecting anomalies caused by deviations from normal behavior as well as changes in operating conditions.

Chen et al. [165] employed binary threshold-based Hotelling's T^2 and Q statistics as anomaly detectors for SiC MOSFETs. The training data comprises both thermal and electrical time-domain features in their healthy state, with deviations from these parameters indicating semiconductor degradation. PCA is used to select key indicators that determine the type of failure, which reduces the dimensionality of the data while maintaining the essential trends.

In [169], He et al. introduced a fault prognostics approach for a three-phase grid-tied inverter. They employed a Gaussian mixture model with two distinct data clusters. The first one represented the healthy baseline, while the second cluster represented an inverter state that is to be predicted. By measuring the difference between the two clusters using the Jensen-Shannon Divergence, a health indicator was constructed for prognostics, triggered when a given threshold is exceeded.

In [160], Pham et al. developed a fault detection and isolation algorithm that uses an Autoadaptive and Dynamical Clustering approach to cluster feature data into classes that characterize normal and faulty operation modes. The classes are labeled based on knowledge of the system, and the similarity between recent feature vectors and the labeled classes is used to detect

and isolate faults [159]. The Mahalanobis distance (MD) [176] is used to measure the closeness between a new feature vector and existing classes in the learning stage. The proposed algorithm also allows for online updating of existing faults and detection of unknown faults. Experimental results demonstrate the method's rapid and effective detection of single and double open-circuit faults.

3) Hybrid methods

Obtaining labeled samples for supervised learning can be challenging for fault detection and diagnosis. Unsupervised learning, while adaptive, often requires a large dataset [170], [177]. Hybrid models combine both labeled and unlabeled data, improving accuracy, especially when human expertise is limited [167]. Some classical hybrid learning methods and architectures include self-training, co-training, transfer learning, graph-based methods, and deep learning architectures such as variational autoencoders (VAE) and combined architectures such as CNN-RNN networks.

In response to the need for hybrid models, Markovic et al. [143] presented a custom approach for monitoring power electronic systems. Building on the work in [178] which focuses on handling modeling uncertainties to enhance fault detection reliability, this work addresses the inevitable problem of intermittent errors in learning-based approaches, which make them impractical for use in real-world systems. To address this challenge, the authors propose a novel hybrid model that integrates neural and statistical components with cross-temporal hypothesis testing. This approach applies sequential methods for multi-hypothesis testing to classify the system's current state, incorporating M-ary sequential probability ratio

tests. This framework delivers complete reliability upon the measurement of selected Buck converter signals. The proposed cross-temporal integration approach achieves 100% classification results for every state, test scenario, and feature vector choice, such that neural classifiers with cross-temporal integration provide an encouraging path forward, combining interpretable instantaneous classifier outputs with statistically derived decision thresholds.

Meta-learning [179] also offers solutions for limited labeled and unlabeled data. It involves training a model for new tasks with limited data by leveraging prior experience from related domains. For instance, few-shot learning, as proposed in [170], harnesses prior knowledge from related tasks to diagnose faults from limited labeled data. The method accurately detects open-circuit IGBT faults in a three-phase converter using data from

both a grid-connected converter and a three-phase PMSM drive converter. By generating synthetic fault samples using a disturbance autoencoder generation model, the method achieves over 95% fault diagnosis accuracy with limited labeled samples, highlighting the potential of few-shot learning and meta-learning approaches for similar challenges.

In [171], a semi-supervised fault detection and diagnosis method for power transformers combines feature extraction and a generative adversarial network (GAN) to address the issue of imbalanced labeled and unlabeled datasets. The GAN [180], consisting of an LSTM-based generator model and a CNN-based discriminator, generates synthetic samples for underrepresented labeled samples. The labeled and unlabeled datasets are then combined to construct a graph network that achieves a high fault classification accuracy of more than 80%.

Table 3. Advantages and limitations of fault clustering and classification methods for power converter applications

	Method			Advantages	Limitations
Clustering	Self-Organizing Map (SOM)			Handles directly high dimensional problems, topological interpretability.	Sensitive to hyperparameters, limited scalability for nonlinear problems.
			[141], [152], [154]		
	k-means			Fast and scalable, few parameters to tune.	Predefined number of clusters, depends on initialization, converges to local optima, accuracy in complex non-linear data.
			[141]		
	Mahalanobis distance (MD)			Robust to outliers, suitable for multivariate data distribution.	Sensitive to covariance matrix estimation, computational complexity increases with data size.
			[153]		
	Interval-based method			Handles uncertainty in data, provides interval-based clustering results.	Subjectivity of interval construction, sensitivity to interval overlapping and similarity metrics, limited interpretability.
			[153], [163]		
	Gaussian mixture model (GMM)			Flexible modeling of complex data distributions, soft assignment of data points to clusters.	Sensitive to initialization, converges to local optima, struggles with high dimensional data.
			[160], [169]		
	Dynamical clustering			Accounts for non-stationary data, evolving clusters, combines the benefits of GMM and MD.	Sensitive to initialization parameters such as the covariance matrix and membership threshold, limited interpretability.
			[159], [160]		
Classification	Relevance Vector Machine (RVM)			Automatic relevance determination, space solution, good generalization.	Computationally expensive, sensitive to hyperparameters.
			[138]		

Feedforward Neural Network [141], [142], [145], [147], [151], [158], [168]	Nonlinear modeling capability, adaptive learning.	Prone to overfitting, requires sufficient training data, black box nature.
Support Vector Machine (SVM) [141], [142], [146], [150], [168]	Low programming complexity, effective in high dimensional spaces, works well with small datasets, global optimal solution.	Hyperparameter sensitivity, computationally expensive for large datasets.
Probabilistic Neural Network (PNN) [142]	Fast training, efficient memory usage, pattern classification.	Limited generalization, low sensitivity to training data.
Naïve Bayes (NB) [142]	Fast training and prediction, suitable for high dimensional data, works well with small datasets.	Assumes independence between features, may not capture complex relationships.
k-Nearest Neighbors (kNN) [164], [168]	Simple implementation, handle multiclass problems.	Computationally expensive during testing, sensitive to noise, requires appropriate distance metric.
Random Forest (RF) [134], [168]	Good performance with large datasets, high dimensional data, resistant to overfitting and outliers.	Interpretability challenge, computationally expensive for high dimensional data or large number of trees, struggles with extrapolating to unseen data.
Neural controlled differential equations [154]	Incorporates temporal dynamics, handles multimodal data, suitable for fusion-derived data accommodating irregularities.	Computationally heavy especially for large dataset, impact of data imbalance on performance, sensitivity to learning rate and batch size.
Convolutional Neural Network (CNN) [173]	Embedded feature extraction capability, spatial invariance, hierarchical representation of data content, ability to capture local patterns.	Sensitivity to hyperparameter selection, limited awareness of the broad relationships within data, computationally extensive.

C. RUL prediction

Data-driven methods have been increasingly applied to predict the RUL of power devices, as model-based approaches lack complete physical representation [181]. RUL estimation involves regression modeling with historical nominal or accelerated data and predicts the time until degradation reaches a failure threshold [132], [182]. In addition to the expected value, it is important to enclose it within a range of uncertainty metrics. Artificial intelligence techniques are commonly employed for RUL estimation. By learning degradation patterns, the regression model can project future degradation levels and estimate the RUL with greater accuracy.

The paper in [161], presents a power IGBT prognostic approach using accelerated aging data from thermally overstressed IGBTs. It employs a feature extraction process and

a maximum likelihood estimator (MLE) and demonstrates enhanced accuracy and robustness, particularly near end-of-life stages.

Another study [183] compared machine learning models for real-time prediction of IGBT RUL under thermal overstress. The Back Propagation Neural Network (BPNN) outperformed other models, including the Random Forest Regressor and Extreme Learning Machine algorithms.

In [184], IGBT RUL prediction combines the gray Verhulst model and the particle filter algorithm. The underlying assumption is the coexistence of two degradation regimes. A slow one, with subtle degradation effects, and a rapid one, directly leading to failure. The gray Verhulst, which is a data-driven method suitable for predicting short and medium-term data, is used to predict slow degradation trends, while the

particle filter algorithm handles rapid degradation owing to the fact that it is suitable for predicting sample data with nonlinear or unstable degradation laws. A double Gaussian function model is used to characterize the state equations for the particle filter and is found to be more accurate than the usual double exponential function model. The two-stage approach improves RUL prediction accuracy, especially for nonlinear and unstable degradation trends.

Table 4 summarizes the main RUL prediction methods and parameter update model of the references discussed in this paper.

Table 4. Comparison of RUL prediction methods

Ref	Model	Model parameter update
[68]	ANN	Minimization of cost function
[185]	Wiener process with linear drift	Similarity measurement
[127]	Zonotopic intervals	Polynomial update
[156]	Stochastic degradation	Bayesian update
[181]	Mission profile based	Linear accumulated damage theory
[182]	Gamma process	Unscented particle filter
[161]	Gaussian process	Maximization of MLE cost function
[183]	BPNN, RF, Extreme machines	Minimization of cost function

V. PHYSICS-INFORMED MACHINE LEARNING

The learning approaches and methods discussed in the previous section have primarily relied on data. While data-driven models may accurately fit observations, machine learning predictions may lack physical plausibility or even be physically impossible. Therefore, it is essential to accommodate both accuracy and interpretability when developing and implementing machine learning models to ensure that they provide reliable and insightful predictions. Moreover, when it comes to learning, it is desirable to make use of all available resources, including prior knowledge and experience. Integrating this knowledge into the learning process can help improve the accuracy and generalization of the models developed [10]. Therefore, it is important to strike a balance

between data-driven approaches and incorporating prior knowledge in order to achieve the best possible results.

There are many approaches that fall under the Physics-Informed Machine Learning (PIML) paradigms, and they serve as bridges connecting the empirical power of data-driven algorithms with deep-rooted physical laws and theories. PIML, as a multidisciplinary field, can be dissected into distinct yet interconnected categories, each tailored to address specific challenges. To navigate this landscape, we classify these methods into two main categories: (i) physics-informed loss functions and (ii) physics-guided architectures, which can be themselves subdivided into many others. The choice of which class to employ for a given problem hinges on a multitude of factors. It takes into account not only the availability and efficacy of existing models but also the overarching computational objectives at play. These objectives encompass priorities such as improving prediction accuracy, enhancing model interpretability, optimizing computational efficiency, or ensuring adherence to known physical principles.

A. Physics-informed loss

In the realm of physics-informed machine learning (PIML), a great insight lies in the ability to utilize a subset of initial data to effectively penalize constraint violations across the input space of the ML model [186]. By incorporating specific information from labeled data and leveraging unlabeled data points, we can regulate deviations from desired constraints in the model's predictions. This powerful approach not only enhances the model's performance but also ensures its adherence to the fundamental physical principles governing the system being modeled. Though most ML training routines would ignore parts of the input space without data, physics-informed training structures can instead enforce general physical knowledge of the system we know to be true.

While many variations and applications exist [187], the most common method is to add these constraint violations directly to the loss function during ML model training. The loss function evaluates how well the model is performing and is minimized by changing model parameters over the training routine. By including knowledge directly in the loss function, the resulting model parameters will be biased towards the embedded knowledge. This can be thought of as a soft constraint, as there is no guarantee that it will be totally satisfied. Rather, the learning task balances the two learning goals simultaneously: improving model agreement with data and adjusting model parameters to follow known constraints. This is useful if the full engineering model is too computationally expensive to simulate repeatedly.

1) Physics-informed neural networks (PINNs)

PINNs are one of the prominent forms of physics-informed loss models. They have been employed owing to the fact that they rely on the neural network backbone, which offers several advantages, such as being a universal function approximator.

The work in [188] leverages the power of automatic differentiation to directly compute derivatives of neural network outputs during training, enabling the inclusion of differential and algebraic equations describing power systems in the training procedure. This approach has been used to model PDEs when model outputs are differentiable with respect to model inputs, and applied to accurately determine solutions of differential equations and estimate uncertain power system parameters. The authors use collocation points, which are discretized points strategically placed within the problem domain, to ensure that the network's predictions adhere to the underlying physics.

Unlike labeled points that provide known target outputs, collocation points do not have explicit labels but are chosen to enforce the governing constraints even when labeled data are limited, enabling the network to capture the physics and generalize well to unseen scenarios. The location and sampling distribution of these points play an important role in improving the performance of PINNs and have been the subject of previous studies. The work in [189] explores various classical non-adaptive sampling methods and other adaptive sampling ones that are seen to improve the sampling efficiency and the accuracy of PINNs, among which the residual-based adaptive distribution (RAD) and residual-based adaptive refinement (RAR) methods are the main ones. Evolutionary sampling has also been proposed to gather collocation points in areas with high PDE residuals with minimal computational burden [190].

The framework in [188] not only demonstrated superior performance in identifying power system parameters but also required fewer data and significantly reduced computation time by up to two orders of magnitude compared to classical machine learning and numerical schemes.

The general form adopted in this work has also been used in similar works, which is a parametrized nonlinear PDE and is presented in equations (3)-(5):

$$\frac{\partial u}{\partial t} + N[u, \lambda] = 0, x \in \Omega, t \in [0, T] \quad (3)$$

$$u(0, x) = h(x), x \in \Omega \quad (4)$$

$$u(t, x) = g(t, x), x \in \partial\Omega, t \in [0, T] \quad (5)$$

here $u(t, x)$ denotes the solution which can be seen as the state variables and $N[u, \lambda]$ is a nonlinear term parametrized by λ and dependent on u and its derivatives. The nature of λ determines whether the problem is an inverse problem where the goal is to identify the parameters that satisfies the equation, or that of a forward problem. This framework spans a range of problems including conservation laws, system dynamics and kinetic equations.

Without loss of generality, a physics-informed equation $f(t, x)$ that enforces physical laws in the description of a system, to which we will refer as auxiliary equation, is defined as in (6):

$$f(t, x) = M[t, x, \lambda] \quad (6)$$

In their formulation, [15] and [191] added equalities (7) and inequalities (8) representing the physical constraints mainly in algebraic form:

$$G(t, x, u) = 0 \quad (7)$$

$$H(t, x, u) \leq 0 \quad (8)$$

By construction, both of the networks $f(t, x)$ and the desired output $u(t, x)$ share the same parameters, but only use different activation functions [188]. Therefore, the shared parameters of the two neural networks are optimized by minimizing the generalized loss function introduced by the physics guided neural network [13], [15], [191]:

$$\theta^* = \operatorname{argmin} \mathcal{L}_u + \alpha_{reg} \mathcal{R}(\theta) + \alpha_{phy} \mathcal{L}_{phy} \quad (9)$$

such that:

$$\mathcal{L}_{phy} = \mathcal{L}_{aux} + \alpha_{eq} \mathcal{L}_{eq} + \alpha_{ineq} \mathcal{L}_{ineq} \quad (10)$$

$$\mathcal{L}_{aux} = \frac{1}{N_r} \sum_i^{N_r} |f(t_u^i, x_u^i)|^2 \quad (11)$$

$$\mathcal{L}_{eq} = \frac{1}{N_g} \sum_i^{N_g} |G(t_g^i, x_g^i, u(t_g^i, x_g^i))|^2 \quad (12)$$

$$\mathcal{L}_{ineq} = \frac{1}{N_h} \sum_i^{N_h} \operatorname{ReLU} \left(H(t_h^i, x_h^i, u(t_h^i, x_h^i)) \right) \quad (13)$$

where the first term in (9) represents the empirical loss which was chosen to be the mean squared error corresponding to the initial data such that:

$$\mathcal{L}_u = \frac{1}{N_u} \sum_i^{N_u} |u(t_u^i, x_u^i) - u^i|^2 \quad (14)$$

with N_u being the batch number of training data. This formulation accommodates in (14) the inclusion of initial and boundary condition equations, if they are relevant to the problem at hand. In scenarios where the number of labeled data points differs from the number of boundary conditions, or initial conditions, the empirical loss function can be decomposed into separate components: the training loss and the losses associated with the other categories mentioned. By breaking down the loss in this way, it becomes possible to assess and optimize each aspect independently, allowing for a more nuanced and targeted approach to model training and parameter estimation.

The second term in (9) represents the complexity of the model and is seen as the structural error. Typically, it constrains the weights of the model using L_1 norm (Lasso regularization) to enforce sparsity, L_2 norm (Ridge regularization) to control the magnitude of the weights, or a combination of both for a convex optimization problem with a sparse and smooth solution.

The third term denotes the physical penalty term as expressed in (10) and is used to enforce the physics of the dynamical system over a finite set of collocation points, for the auxiliary equation N_r as in (11), the equalities N_g in (12), and inequalities N_h in (13). The *ReLU* function in (13) is one way to measure the violation of the inequality constraints and has been used widely [191]. The hyperparameters $\alpha_{reg}, \alpha_{phy}, \alpha_{eq}, \alpha_{ineq}$ can be adjusted using grid search techniques [192], [193] or Lagrangian optimization [194]. Note that since the term representing scientific consistency does not require actual observations of the target variable $u(t_u^i, x_u^i)$ but depends only on the estimate f , the method is also well suited for unlabeled data instances, in contrast to traditional loss functions.

With this formulation, PINN can also be implemented in physical simulations, replacing ODE solvers and performing identification tasks. For example, the study in [195] reports that PINNs can approximate any continuous function with a desired degree of accuracy, which is completely opposite to what we are used to with the classical model order reduction approaches in time-domain simulations. The PINN training process incorporates the governing differential equations and an implicit Runge-Kutta (RK) integration scheme, which allows the model to predict the behavior of a dynamical power system at any discrete time step. The trained Runge-Kutta-based PINNs (RK-PINNs) can evaluate the dynamics of a system up to two orders of magnitude faster than standard time-domain simulations without requiring any simulation of training data.

It is worth noting that this loss formulation was first employed with the widely used stochastic gradient descent method (SGD) with fixed learning rate as in [195], however in practice, there are many caveats to using it that are related to unbalanced back propagated gradients during the training. Many methods have been designed to counteract those instabilities, such as the learning rate annealing (LRA) [196] as it dynamically modifies the learning rates for different components of the objective function during gradient descent in order to account for the

inherent difficulty in optimizing under equality constraints. Other methods have looked into modifying the optimization framework rather than changing the underlying optimization method. This includes the self-adaptive method for PINNs (SA-PINN) that employs trainable adaptation weights at each training point that allow PINNs to autonomously identify and focus on the challenging stiff regions of PDE solutions [197]. In contrast, the Augmented Lagrangian relaxation method, termed AL-PINNs, takes a different approach [198]. It handles the initial and boundary conditions of the PDE and relaxes them into the objective function through Lagrangian duality. The constrained optimization problem is thus transformed into a sequential max-min problem. Another method has looked into the issue of accuracy of soft constraints in standard PINNs and proposes a gradient enhancement (gPINNs) [199] for smooth PDEs that not only enforces the PDE residual to go to zero, as it is the case with the formulation presented, but also enforces the derivatives of the residual to be zero as well. The issue of accuracy was treated as well using hard constraints within the hPINN framework, enforcing the constraints using the penalty method [200].

Fig. 13 presents a versatile framework for a physics-informed neural network architecture, including the discussed elements above. This implementation offers flexibility in accommodating different types of governing constraints, which can be mathematical equations, simulation parameters, or even derived from neural networks themselves. This architecture allows notably for leveraging varying degrees of knowledge about the governing equations, enabling flexible modeling approaches. The regularization term is formulated as a combination of Ridge and Lasso penalties, which serve as effective means to control the complexity of the model and prevent overfitting. However, it is worth noting that there are other implemented techniques that can be tailored to further enhance the regularization performance.

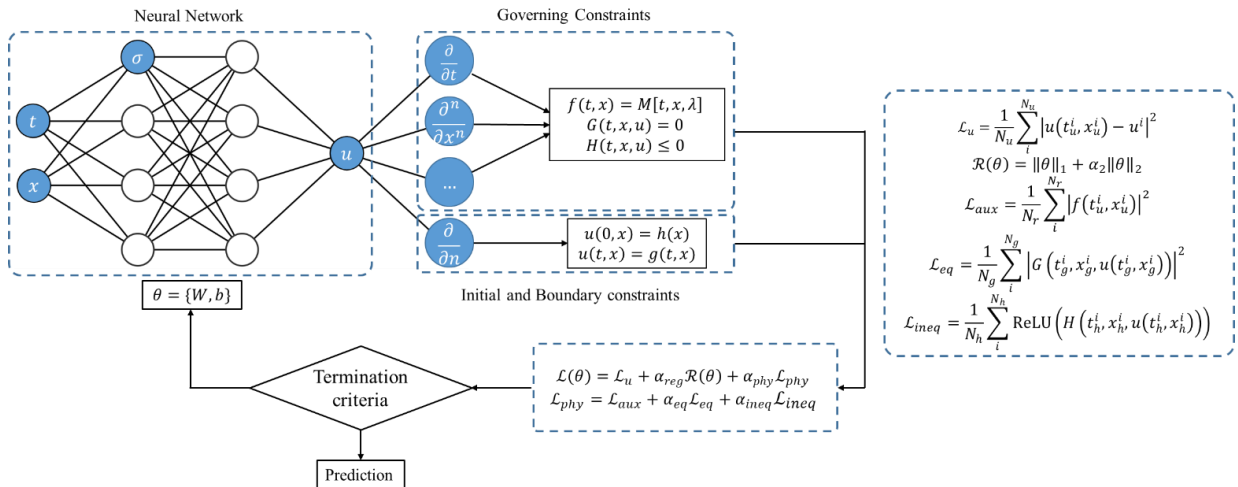


Fig. 13. Generic physics-informed neural network architecture.

2) Gaussian processes

Among ML models, Gaussian Process architectures stand out for incorporating physical knowledge as constraints. Recent research has delved into the integration of physical constraints and prior information within Gaussian Process Regression (GPR) to augment datasets with limited information and effectively regulate model behavior. GPR's widespread acclaim stems from its versatility and capacity to provide closed-form predictions, making it one of the favored choices for predictive maintenance.

In his work [201], Agrell presented a framework that encodes sets of linear constraints, whether they be monotonicity, convexity, or boundedness to the GPR, with sampling-based inference that is suitable for developing ML models for safety-critical engineering applications. In [202], Swiler et al. surveyed ways by which constraints can be implicitly enforced through tailored sample space constructions, modified covariance kernels, or adjustments to the output or likelihood of Gaussian processes. In another study [203], a novel machine learning approach that combines PDEs and sparse measurement data is introduced, relying on GPR to address data scarcity. The method integrates physical knowledge from both linear and nonlinear PDEs into the learning process. Similar to collocation points in PINN design, the paper also introduces an active framework for the optimal design of PDE points, effectively leveraging PDE information based on the GPR model and measurement data. An expectation-maximization algorithm is developed for parameter estimation and PDE point selection in this context. In [204] a maximum likelihood estimation for GPR hyperparameter estimation using well-established differential equations is used to ensure physical consistency in inverse problems, with applications in model validation and health monitoring. In another study [205], physics-based penalization terms have been incorporated into the marginal likelihood function for kernel parametrization as a way to instill physics-based knowledge to the machine learning model. Results have shown that the method improves prediction performance, mitigates overfitting problems, and captures underlying physics.

B. Physics-informed architecture

Within the domain of PIML, the architecture of machine learning models holds a crucial role in bridging data-driven techniques with prior physical knowledge. These physics-informed architectures take diverse forms, designed to match specific problem characteristics. They can, for instance, embed physical properties directly into the model's nodes and layers, enhancing interpretability. Physics-informed activation functions can also be seen as mirroring physical behaviors, rendering the model physically consistent. Hybrid PIML models combine physics-based models with machine learning, integrating differently domain knowledge with data-driven techniques, while Bayesian PIML framework quantifies uncertainties and incorporates various prior knowledge forms.

In this section, we explore these architectures, focusing on their design variations and applications, particularly within neural networks, where they are mostly used.

1) Embedding physics in ML

Physics-informed architectures empower machine learning models by seamlessly incorporating established physical principles. These architectures adapt to the model's structure, harnessing techniques like neural networks to actively encode prior physics knowledge into the architecture. This process entails crafting nodes or layers that directly represent recognized physical phenomena, setting them apart from physics-embedded loss functions, which passively constrain network training through specific physical equations.

In [206], a Physics-Informed LSTM (PI-LSTM) architecture is presented as a combination of a physics-based calendar and cycle aging (CCA) model with an LSTM layer. The emphasis is on leveraging the entire layer's capabilities to capture relationships between degradation and operating conditions. This integration involves incorporating physics-based knowledge into the structure and behavior of the LSTM layer to improve battery health modeling and RUL prediction.

In [207], the authors introduce a novel approach to machine degradation modeling that integrates signal processing techniques with a neural network structure. The proposed network comprises several hidden layers designed to process temporal signals, directly linking the network with fault frequencies and their harmonics in the frequency domain. This approach enhances transparency, interpretability, and the stability of health indices used in predictive maintenance. It combines physics-based methods with machine learning, providing structural and weight interpretations for better machine health monitoring and prognostics.

The work in [208] introduces a novel method for battery capacity prediction that directly incorporates physics-based insights into machine learning models. It utilizes a specialized neural network architecture, the aging mechanism-informed bidirectional LSTM, to integrate physics principles. The aging mechanism layer is made of LSTM cells to identify related features. This approach results in faster, more accurate predictions with broad application prospects, surpassing the best-performing data-driven benchmark by a significant margin of 50%.

Gokhale et al. [209] developed two distinct physics-informed prediction frameworks that integrate fundamental physics principles into a DNN. In the first approach, a dedicated dynamics module is designed to incorporate the physics of the system. This module utilizes encoded latent representations of high-dimensional state inputs, along with observable state information, actions, and other external data, to predict the subsequent observable state. Importantly, the encoded latent representation is influenced by the system's underlying physics,

ensuring that it contains vital information pertaining to the system's dynamics. The second employs a conventional neural network with physics knowledge incorporated through specific equations, using a latent representation as a regularization term to guide learning of system dynamics and hidden parameters. These architectures enhance machine learning models with physics information, offering different approaches for integrating physics within the neural network structure. Notably, these models have demonstrated remarkable accuracy improvements, yielding three times less error in predicting hidden state variables in the latent space compared to their data-driven counterparts.

In another study, a PINN-based online impedance identification of voltage-source converters (VSCs) under changing operating points was developed [166]. The proposed method is specifically designed to address the issue of limited data availability for online impedance identification, which is crucial for the online stability evaluation of VSCs. To overcome this limitation, the PINN is constructed based on the derived analytical impedance model of VSCs, which takes Park's vector transformation of the three-phase currents, voltages, and frequency as inputs to account for the changing operating points. The neural network can thus have a shallower representation with a smaller number of layers and fewer neurons per layer, reducing the number of parameters that need to be trained and the computational complexity of the network. This makes online impedance identification faster and more efficient while maintaining accuracy. By employing a two-step impedance identification approach based on transfer learning theory, the efficiency of the methods is improved. This is achieved by enhancing the online impedance identification efficiency through the transfer of the offline impedance model to online impedance identification of different VSCs.

Neurons can also be tailored towards embedding physics, for example, [206] uses a custom LSTM cell that extracts functional information from the monitoring data and feeds specific cells and gates as in a standard LSTM cell. In [210], each RNN unit is made of a combination of physics-based, data-driven and Bayesian nodes. In another study [9], LSTM cells incorporated augmented and hidden states to better capture the state of charge of batteries.

2) Physics activation function

Just as neurons can be physics-informed, so can model mechanisms such as activation functions and initialization procedures [211]. The choice of activation function has a significant impact on the success of training PINNs to solve PDEs. While common activation functions such as sigmoid or \tanh may suffer from the vanishing gradients problem, $ReLU$ function on the other hand, does not suffer from this problem but poses challenges with regard to its PINN use [212]. For integrating physical knowledge, it is sometimes necessary to take high-order derivatives of the NN with respect to network inputs to calculate the loss function. However, higher-order

derivatives of $ReLU$ are equal to zero, and this makes the training process ineffective.

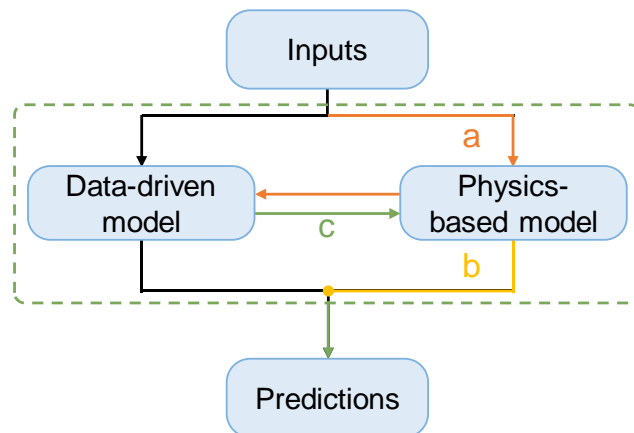


Fig. 14. Different hybrid integrations: a) combination approach, b) output combination and c) physics-based enriched model

The study in [213] evaluates the effectiveness of PINN in predicting out-of-distribution testing data [214]. The results indicate that PINNs struggle to predict out-of-distribution data, consistent with previous findings. To address this issue, the study proposes the replacement of the generic activation functions by the customizable Physical Activation Functions (PAFs) that are inspired by the physical behavior of the investigated phenomena. PAFs are theoretically based on the analytical solution of the physical phenomena being studied, meaning the AF resembles and takes the form of the expected physical response if such information exists, or can be obtained under simpler assumptions from the initial or boundary conditions of the system. For example, let's assume that the physical solution to a problem is a multivariate function $f(x_1, x_2, \dots, x_n)$ that is the sum of two other functions g and h that are only partially known, a PAF σ can be designed with fewer variables $\sigma(z_1, z_2)$ such that the PAF has the global behavior of the function g . Following this construction, several PAFs can be included in the same model, one for g and another for h , continuing with the previous example. Similarly, if an initial or boundary condition function is partially known, PAFs can be constructed the same way.

PAFs make PINNs more physically constrained as compared to NN without physical loss and PINNs with generic activation functions and can therefore be seen as a complement to the PINN architecture. This reduces the errors of out-of-distribution predictions, and helps reducing the training complexity of PINNs. PAFs are shown to improve the extrapolation capability of PINNs for domains that are out of training range, and reduce the size of the network by up to 75%, a size where they are the most effective. Furthermore, the use of PAFs reduces training complexity, decreases the loss term by up to 2 orders of magnitude, and reduces the computation time to facilitate the implementation of PINNs in real-world applications. The study concludes that the use of PAFs offers a

more physically constrained and valid approach to PINNs, enabling accurate predictions for longer ranges.

A diverse collection of PAFs may also be employed to create a broader search area, which includes a reservoir of potential activation functions [215]. Instead of selecting a single function, the adaptive activation function is created using physics-informed activation function (PIAC), where a set of candidate functions is linearly combined with optimized coefficients. PIAC allows the neural tangent kernel of PINNs to be trainable, leading to a noticeable improvement in performance. Similar methods of the physics-based activation function have been implemented in power systems [216].

3) Hybrid modeling

Traditional approaches often grapple with incomplete physics-based models and limited representative training datasets, posing significant challenges to achieving accurate predictions for complex real-world systems [217]. In response to these challenges, Hybrid PIML allows for more accurate, robust, and interpretable models. Many hybridization techniques exist, such as the one that allows concurrent operation of physics-based models and machine learning models before merging both of their outputs for decision-making or the one using them sequentially, or the one combining both and many other (Fig. 14). This adaptability positions Hybrid PIML as an invaluable tool in scenarios marked by data scarcity and the pivotal role of physical principles. By virtue of these strategies, hybrid PIML not only finds application in enhancing predictive accuracy but also extensive utility in constructing surrogate models and facilitating numerical simulations.

For example, a framework presented in [218] controlled physics-informed data generation with deep learning-based prognostics. It introduces a controlled physics-informed GAN to produce synthetic degradation trajectories aligned with underlying physical laws. These synthetic trajectories enhance the accuracy of RUL predictions by more than 17% compared to baseline data-driven methods, especially when real time-to-failure data is limited and does not cover all relevant operating conditions. Key components of the framework include surrogate models to infer health parameters, and the GAN that builds on the TimeGAN generation framework [219] and adheres to basic physics constraints and maintains physical consistency. It leverages deep neural networks and synchronization techniques for robust generation of synthetic time-to-failure data. Future research avenues include pro-active data generation based on prediction uncertainty and extending the framework to various application domains, highlighting its versatility and potential impact in predictive maintenance scenarios, whether for condition monitoring or, more importantly, RUL prediction.

The study of hybrid PIML expanded to the area of model identification for power converters. It allows the discovery of governing equations [220] and underlying models that describe

the behavior of a physical system, with the aim of gaining a deeper understanding of the system's behavior. In this sense, a scalable and permutation invariant graph neural network for circuit identification is proposed in [221] with a proper feature representation model for electric circuit parameters. The method suggests an optimal feature representation based on bond graphs that can be easily interpreted and processed by machine learning algorithms, regardless of the connection or the number of components the circuit has. This technique is based on bond graph representation for circuit synthesis, which can also be valuable for simulating power converters.

Another approach to condition monitoring hybridization is presented in [9], which integrates physical knowledge by decoupling voltage signals into open circuit voltage, polarization voltage, and ohmic response components. This augmentation of input data enables the employed DNN to better understand battery voltage characteristics, improving the state of charge (SOC) estimation root mean square error by over 30%. Another key enhancement involves introducing ampere-hour counting information, which reflects the SOC change between two adjacent moments. Traditional DNN-based methods overlook this physical information. By incorporating the Ampere-hour counting information through an online Kalman filter and Monte-Carlo dropout technique, the DNN can provide not only SOC estimates but also their associated uncertainties, resulting in more precise and reliable SOC estimations.

In [222], a hybrid PINN combines concepts from CNNs and finite volume methods to solve PDEs. Unlike traditional PINNs, this method employs a differential operator approximation instead of automatic differentiation, contributing to improved convergence rates and prediction accuracy. This marks a significant advancement as it introduces the concept of a convergent rate in machine learning-based PDE solvers, akin to numerical methods. Furthermore, this hybrid PINN exhibits versatility, catering to various problem domains, including surface PDEs and inverse problems. It offers higher accuracy and maintains adaptability even when boundary conditions or right-hand side terms change, making it suitable for transfer learning and parallel learning. While it inherits the robustness of numerical methods, there are considerations for stability, particularly in the context of parabolic and hyperbolic equations, where the local fitting method's stability may need further attention. Nevertheless, the Hybrid PINN presents a promising fusion of machine learning and numerical techniques for tackling complex PDEs efficiently and accurately.

The paper in [223] introduces a Finite Element Mimetic Neural Network, a hybrid PIML model designed for fault detection and localization. It combines finite element methods with machine learning techniques. The model leverages physics parameters and raw vibration acceleration signals for input, incorporating known physics relationships. The hybridization of the model involves the integration of finite element methods

with NN layers. Unlike traditional FEM, which relies on complete analytic physical knowledge and parameter values, this framework takes advantage of partial knowledge, which includes partially known parsing relationships and parameter values. This hybrid approach combines the strengths of FEM, which captures physical principles, with the flexibility and adaptability of neural networks. It allows the model to leverage physics-based knowledge without being restricted by the need for complete analytic solutions. Instead, it combines the physics-based output with data-driven adjustments to enhance the model's diagnostic capabilities. Experimental validation demonstrates that the model's total accuracy surpasses that of the non-physics-informed ML model by over 130%.

In [224], a Physics-based Neural Network (PbNN) is utilized to construct a physical model for an industrial control system (ICS) by integrating the underlying physics and operational data. PbNN is specifically designed for real-time settings and employs the residual sequence generated by the comparison of the actual and predicted values to quantify nonrandom hence physical patterns to detect anomalies. The PbNN enables live detection of both sequential and concurrent anomalies, achieving a remarkable 100% detection rate and 0% false alarm for tested cases, offering more accurate results compared to state-of-the-art methods that solely rely on data-driven approaches. The PbNN is constructed through a two-phase process. In the offline phase, the interactions among the state variables of the system under study are modeled using a CNN. The latter is trained using collected operational data, which aims to capture the complex relationships among the state variables that are extracted using mathematically modeled components. The CNN, which is commonly used for image and speech recognition, is used in this case to model the interactions among the state variables of the ICS. Once the CNN is trained, it is used in the online phase of the PbNN method to detect anomalies. In this phase, the expected behavior of the ICS is obtained from the CNN, and any perceived deviation between the actual and predicted behavior is flagged as a fault. Specifically, it utilizes a statistical approach to detect nonrandom physical dynamics. Anomalies are detected by characterizing patterns in the residual sequence that stems from the comparison of actual and predicted values. To quantify the magnitude of residues, the CUMulative Sum (CUSUM) approach is integrated with the CNN. CUSUM uses the time sequences of the predicted and observed states to detect abnormal deviations corresponding to process anomalies. By computing the CUSUM of the residual sequence, even minor deviations in magnitude can be detected.

Another study presents a modeling approach for planar magnetic components based on a knowledge-aware ANN, which integrates small training data with specific domain knowledge [225]. The proposed ANN employs two types of input data with different properties: measured or simulated data with high accuracy but limited amount, and analytical data with lower accuracy. By synergistically combining the measured

data and analytical models, two ANNs are trained to build a correlation between the analytical models and the optimal mapping function that serves as a regression tool. In this framework, the analytical models initialize the mapping and remove nonphysical results. The proposed method is compared to existing modeling tools and demonstrates improved performance with regard to the balance between accuracy and computational efficiency, particularly in reducing errors associated with measured data, which are mainly located around 3%. This is notably different from the broader error density within 20% for both the purely analytical and purely data-driven models.

4) Bayesian PIML

In the domain of predictive maintenance, a pivotal requirement extends beyond obtaining precise diagnostics and prognosis predictions; it involves understanding the associated uncertainties. This necessity has prompted the development of various methods for reliability inference, including Bayesian Networks, Universal Generate Function, Fault Tree Analysis, and others [226]. Among these, Bayesian Networks have gained considerable popularity, recognized for their robustness and efficacy.

Building upon the PIML foundation, Bayesian PIML retains the fundamental strengths of PIML but introduces Bayesian statistics into the framework. This enhancement allows Bayesian PIML to not only serve as a prior in a general Bayesian Inference but also generate estimators for posterior distributions, thereby offering valuable insights into uncertainty quantification [227]. The comparative advantage of Bayesian PIML, when measured against its traditional counterpart, is its capacity to provide narrower credible intervals. This attribute significantly enhances predictive potential, particularly when venturing beyond the boundaries of the training data. However, it is important to note that while Bayesian PINNs offer substantial advantages, they do come with increased computational cost. Nonetheless, their versatility, combining the strengths of various methods, makes them an invaluable tool for tackling a wide array of nonlinear dynamical systems. Linka et al. [227] also discuss the inherent advantages and disadvantages of different methodologies within the NN and Bayesian inference families and provide valuable guidelines for model selection. The integration of physics principles within the Bayesian PIML architecture enables effective modeling even with limited data, while the statistics enrich the toolkit by offering a deeper understanding of uncertainty (**Fig. 15**).

The work in [226] explores a novel approach for reconstructing the temperature field of a high-density functionally integrated satellite circuit board and quantifying data uncertainty. Traditional deep learning models like the CNNs often require extensive labeled data, which is impractical for real-world satellite engineering scenarios where only noisy, unlabeled data is available. To address this challenge, the paper presents a physics-informed deep Monte Carlo quantile

regression method. This unsupervised technique combines a CNN with known physics knowledge to accurately reconstruct the desired temperature field using solely monitoring point temperatures. Moreover, this approach quantifies temperature data uncertainties through the application of Monte Carlo quantile regression. This information feeds into the Bayesian network, enriching its ability to model reliability under conditions of uncertainty.

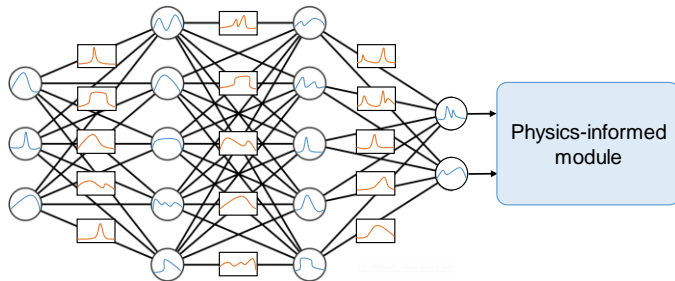


Fig. 15. Example of Bayesian PIML in a NN integration, with probability distribution estimates over the activations (blue) and for the weights (orange)

The research [210] introduces a Bayesian PIML framework that seamlessly integrates physics-based knowledge with machine learning techniques to ultimately deliver robust and reliable RUL estimates. It first integrates temporal dependencies and the physical governing equations within a RNN, enabling accurate simulations of battery behavior under varying operational conditions. To capture model-form uncertainty inherent in real-world scenarios, multi-layer perceptrons are employed, enhancing the predictive power of the framework by addressing deviations from pure physics-based modeling. Leveraging Bayesian principles, the framework integrates data from a fleet of similar batteries as informative priors, enriching the understanding of battery health and performance using variational multi-layer perceptrons. A unique strength lies in quantifying aging uncertainty, even in cases where comprehensive usage history data is lacking, enhancing the practicality of RUL estimation for in-service fleets.

C. PIML for predictive maintenance

Predictive maintenance is a critical aspect of ensuring the reliability and longevity of complex systems across various industries. Traditionally, predictive maintenance methods have leaned heavily on data-driven approaches, where failure states are predicted using machine learning models. Incorporating PIML strategies into predictive maintenance frameworks can significantly enhance their effectiveness. Predictive maintenance encompasses a wide range of tasks, including fault diagnosis, degradation modeling, RUL prediction, health management, and maintenance scheduling.

1) Fault diagnosis and condition monitoring

Predictive maintenance aims to predict when equipment or machinery is likely to fail so that maintenance can be performed

just in time, minimizing downtime and costs. In predictive maintenance, continuous monitoring of equipment health and diagnosis of faults is crucial. In [228], condition monitoring is approached from the perspective of data compression, as efficient data transmission is arguably one of the most important aspects of predictive maintenance. The study uses Deep Convolutional Autoencoders with local structure and physics-informed loss terms that incorporate domain-specific knowledge, such as the importance of frequency content for fault diagnosis. This aligns with the idea of enhancing machine learning models with physics-informed constraints. Additionally, the paper proposes the use of Fault Division Autoencoder Multiplexing to mitigate the effects of multiple disjoint operating conditions on data reconstruction. This is an extension of the PIML approach to address the challenges posed by diverse machine conditions.

In [229], parameter identification of a DC-DC Buck converter is being investigated using a PINN framework. The PINN combines a DNN and the dynamic models of the converter, effectively coupling the data-driven part and physical model part. This method employs supervised learning and is capable of estimating the component parameters of the converter, given the collected data of the inductor current and output voltage during transient behavior due to load changes. The proposed method utilizes a peak-to-peak sampling mechanism to enable efficient data acquisition and to infer the switching state of the converter, significantly reducing the data requirements for training, and highlighting the data-light characteristic of the method. The PINN model comprises two parts: a data-driven component and a physical model component. The former employs a DNN with various hidden layers and neurons, taking in initial states of the inductor current, output voltage, switch state, and time period as inputs. Its outputs are the latent states of the inductor current and output voltage, which are passed on to the physical model component. This second part is formulated using the q-stage Runge-Kutta scheme and the dynamic model of the Buck converter. Notably, the connection between the two components differs in that the former's hidden layer connections depend on neural network weights, while the latter's connections depend on equations with physical implications. In addition, the training error variation is consistent while the average estimation error remains below 0.1%, even for cases with disturbance factors such as ADC quantization error, noise immunity capability, and synchronization error.

The study in [230] employed a PINN technique to monitor the state of a DC-DC power system. The deep learning model was augmented with a state space model as prior knowledge to estimate the degradation parameters of the DC-DC converter. To capture temporal dependencies in the data, the LSTM architecture was chosen as the data-driven model, resulting in a PI-LSTM network that utilizes the output voltage and inductor current as inputs. The output voltage, which represents the operating state of the Buck converter, and the inductor current,

which represents the input current of the circuit, are used to estimate the capacitance, capacitor equivalent resistance, inductance, inductor equivalent resistance, and triode on-resistance parameters.

To enhance the performance of the PINN in solving the physical equation of the Buck converter, the study proposed a multi-task learning approach that shares data sets and low-level features across tasks. A task-based uncertainty determination coefficient strategy was also adopted to optimize the weighting coefficients of the data fitting and physical law fitting subtasks in the multi-task loss function, enabling an adaptive fusion of data and physical knowledge. This approach proved useful in addressing the challenge of limited data, where the uncertainty-based weighting approach balances the contribution of data fitting and physical information fitting tasks. The proposed PI-LSTM model demonstrated superior reliability, higher estimation and generalization abilities compared to the LSTM model, particularly in cases of scarce data, where it showed a 20% error reduction.

Yan et al. [207] propose an architecturally explainable network for machine degradation modeling, emphasizing the integration of physics-based signal processing techniques and machine learning in a single-layer network structure. This approach enhances the interpretability and transparency of health indicators used in machine diagnostics and prognostics. The network utilizes signal processing methods like Hilbert transform and Fourier transform to map temporal signals into demodulated signals, directly linking the network with fault frequencies. A knowledge-guided loss function is introduced for feature extraction for improved health indicator stability and robustness compared to existing methods.

Other studies have applied the different PIML frameworks presented for fault detection and diagnosis. For example, the study in [231] proposes a physics-informed deep learning approach for fault detection. The takeaways from this approach include a threshold model that assesses health classes based on known physics and a deep CNN model that extracts high-level characteristic features from the input data. The unique aspect is the use of a customized data-and-physics-driven loss function that selectively amplifies the effect of physical knowledge assimilated by the threshold model when embedding this knowledge into the CNN model.

In [232], Wu et al. implemented an unsupervised anomaly detection approach that uses a physics-informed gated recurrent graph attention unit network. The key innovation lies in combining prior knowledge into a topological structure to enhance model performance and interpretability. A physics-informed learning module explicitly models variable dependencies in a directed graph, introducing prior knowledge as graph regularization to align the model with the underlying physics. Subsequently, the attention unit network is proposed to capture both structural dependencies between variables and temporal dependencies of each variable, improving anomaly

sensitivity. The work allows for better interpretability and localization of detected anomalies, especially in high-dimensional data, where the F-score is improved by more than 30% and recall by more than 40%, as compared to other purely data-driven methods.

The architecture proposed in [233], is a multi-task deep learning framework. It leverages synthetic data generated by physics-based simulations and integrates domain-specific physical parameters into the loss function. Simulated finite element method responses in the time domain serve as input, and physical parameters such as natural frequencies and mode shapes, known damage indicators, are used to train the intermediate layers of the network. This architecture effectively combines the strengths of neural networks with physics knowledge, enabling generalized damage detection and localization in dynamic systems. It operates based on structural response measurements obtained from simulated models and is adaptable to various damage scenarios, enhancing the damage classification accuracy, especially as the modeling error increases with improvements of over 10% compared to black-box models.

When dealing with diagnostics, training and test data often differ in operating scenarios. The study in [234] introduces a physics-informed feature weighting technique. This approach leverages prior physical knowledge related to faults to extract robust and distinguishing features that remain resilient to variations in operational parameters. Specifically, it incorporates a unique physics-informed feature weighting layer, which enhances the model's sensitivity to features associated with faults. Similar to an attention mechanism, the weighting layer assigns higher importance to features relevant to fault conditions. By imposing constraints on the distribution of feature weights, prior physical knowledge is seamlessly integrated into the model.

2) Prognostics

In the domain of RUL estimation, PIML has emerged as a powerful approach to enhance the accuracy of predictive maintenance methods. Traditional data-driven approaches utilizing neural networks often yield unreasonable RUL estimates due to a lack of consideration for the physical properties of the system.

For instance, Lu et al. [235] present the integration of PINN into RNN based RUL estimation methods. By incorporating monotonicity and boundary condition constraints into the neural network's loss function, the experiments conducted over an IGBT dataset, the first application of its kind to estimate the RUL of power electronic devices, reveal significant improvements in regression performance, as indicated by improved Mean Square Error and coefficient of determination in comparison to baseline RNN methods.

The paper in [206] discusses a new approach to modeling battery degradation and predicting the RUL of batteries under varying operating conditions. The work focuses on the integration of a physics-based calendar and cycle aging model constructed from various other stress sources into a machine learning framework made of a custom LSTM layer, as discussed in the previous section on physics informed activation functions. The approach is demonstrated using experimental data, showing accurate state estimation that outperforms state-of-the-art data-driven methods by up to fivefold in degradation modeling, while RUL estimation conducted with the physics-informed model provides accurate results.

In [217], a hybrid PIML framework is utilized to derive the RUL of safety-critical systems. The hybrid framework merges the strengths of physics-based performance models with deep learning algorithms for prognostics. Within this framework, physics-based models serve to deduce unobservable parameters linked to the health of the system's components through a calibration process. These inferred parameters are then integrated with sensor data and serve as inputs for a DNN. This fusion results in a data-driven prognostic model enriched with physics-derived features. Experimental results demonstrate the superiority of the hybrid approach compared to purely data-driven methods, extending the prediction horizon by more than 120%, while offering greater robustness with less reliance on extensive training data, making it less sensitive to dataset representativeness issues.

The work in [236] presents a health prognostics approach, addressing the challenges of predicting the RUL under complex systems' physics and external operational conditions. A knowledge-constrained machine learning framework is introduced to model the stochastic degradation of battery performance over working cycles. The method points out a synchronized Kalman-Filter and ANN combination as a diagnosis tool that extracts battery's health information. Then a knowledge-constrained Gaussian Process method is developed, incorporating prior knowledge about battery capacity fade as additional constraints. These constraints enhance the fidelity of machine learning models, leading to improved RUL predictions during operation.

Another study looked at RUL estimation using multisensory data under dynamic operating conditions and multiple failure modes [237]. It combines the auto-regressive moving average (ARMA) mechanism with a graph convolutional network and gate recurrent unit for efficient information extraction. The method incorporates maintenance physics-based knowledge into the loss function, ensuring high-fitting accuracy with strong security. **Fig. 16** summarizes the main application areas of some prominent PIML models.

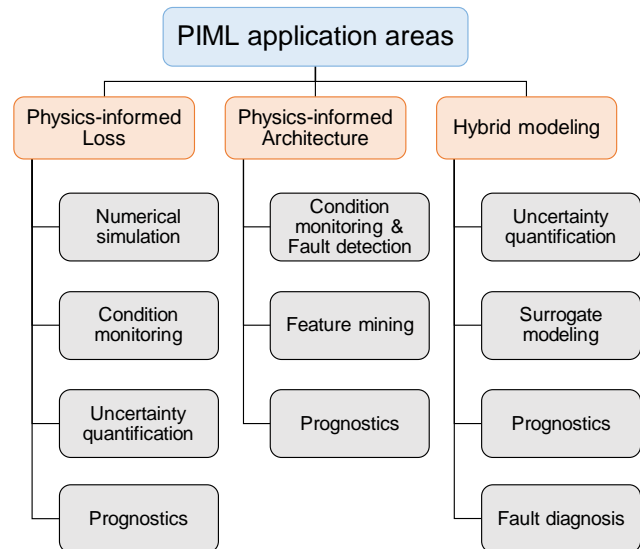


Fig. 16. Application areas of main PIML models for predictive maintenance

VI. CONCLUSION AND PERSPECTIVES

Knowledge of the degradation mechanisms under different stresses is important to gain a fundamental understanding of driving forces of power converter failures, and to design appropriate strategies for predictive maintenance. Huge effort has been spent on understanding the underlying mechanisms from a component perspective, based on failure experiments and accelerated aging. Following the development of scientific paradigms, maintenance strategies have gone through empirical, physics-based, and data-based modeling, with remaining shortcomings of accuracy, applicability, resource allocations, and comprehensiveness.

PIML-based modeling has great potential to overcome those challenges. PIML is a rapidly growing field that combines the strengths of machine learning and physics to solve complex problems. In the context of predictive maintenance, PIML techniques have emerged as a promising approach for improving the reliability and performance of power converters. This work discussed many ways in which PIML can be used to participate in the predictive maintenance effort for power converters. Encouraging results have been coming so far, but there are more research directions in which PIML can be beneficial including model reduction, inverse modeling, and synthetic data generation. As we go towards integrating physics in the machine learning models for complex and multiphysical systems such as power converters, the activity of predictive maintenance needs to rely on understanding the complex degradation mechanisms. However, obtaining reliable data is a challenge in this field, often limited to electrical and temperature parameters. To address this, we need a holistic approach, considering parameters beyond electricity and temperature. These include humidity, vibrational characteristics, including acoustics and ultrasounds. High-quality, diverse data is crucial for robust predictions,

particularly in complex models prone to overfitting such as PIML models.

In the same way, and while PIML strategies have become indispensable for modeling complex system behavior, they have, thus far, not received sufficient attention in terms of data collection and adaptive sampling strategies. The location from which samples are collected, whether for experimental data acquisition or numerical sampling for solving PDEs, significantly influences convergence and accuracy. Deliberate considerations in this regard are imperative. This pursuit for more comprehensive data inherently presents challenges in data storage and processing speed, especially when dealing with fast-paced dynamics. Advanced compressed sensing (CS), with a focus on representing key physical characteristics, becomes indispensable in managing these limitations effectively.

Besides, for more robust predictive maintenance solutions, we need to elevate our understanding of system-level physics. Often, there is an imbalance between component-level and system-level physical knowledge. The more insights we glean into broader system physics, the more adeptly we can harness various PIML frameworks, harmonizing them to make predictions that are more accurate.

If we take a closer look at PIML models, we can see that those employing physics-informed loss functions or hybrid models, that combine physics-based and data-driven models, often rely on empirical ways to determine the weights of the multi-task learning formulation. There is a clear need for comprehensive studies and guidelines to establish principled weight determinations.

Moreover, the inherent complexity of PIML methods, which integrate various types of constraints, demands dedicated optimization techniques. Traditional optimizers may falter when confronted with these intricate problems, and although we have presented many different optimization techniques, they have been developed particularly for PDE solving, but knowledge sources are not just PDEs, therefore there is an increasing need for optimization strategies tailored explicitly to PIML methodologies with various knowledge inputs. These optimized approaches promise improved performance and accelerated convergence.

Another promising research avenue is the continuous update of predictive maintenance models with new observations, drawing inspiration from data assimilation techniques for example. This adaptive approach ensures that predictive maintenance models remain attuned to evolving real-world conditions. This can further enhance the capabilities and accuracy of uncertainty quantification methods over time as new predictions inform the prior probability distributions of inputs, directly benefiting maintenance professionals that are as interested in the predictions as the associated uncertainties.

Also, from a practical angle, hybrid models show remarkable versatility, capable of learning from limited labeled data. They emerge as a very promising tool to bridge the gap between measured and simulated data, a common challenge in predictive maintenance and especially for expensive to label and diagnose systems such as power converters.

Furthermore, embedding PIML algorithms at the edge holds the potential to revolutionize online predictive maintenance. By developing edge AI frameworks tailored for PIML, we can enhance performance and address the critical concerns surrounding data privacy.

Lastly, there is immense scope for leveraging predictive maintenance insights for control strategies. Techniques like reinforcement learning or model predictive control can help optimize power profiles and load distribution depending on the prediction outputs, ensuring cost-efficient maintenance planning while accommodating external factors like supply chain disruptions or weather forecasts.

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