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Review

A review on application of machine learning-based methods for power system inertia monitoring

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ABSTRACT

The modernization of electrical power systems is reflected through the integration of renewable energy resources, with the ultimate aim of creating a carbon–neutral world. However, this goal has brought new and complex challenges for the power system, with one of the most crucial issues which is the reduction of system inertia. The decrease in system inertia has led to severe difficulties in maintaining frequency stability. As a result, power system operators must continuously monitor the system inertia and when necessary to activate appropriate preventive measures, ensuring a reliable and secure operation of the power system. Fortunately, wide-area monitoring systems can provide the necessary measurements to monitor and analyze system behavior, assisting system operators in undertaking optimal actions. This paper provides a review of recent publications that apply machine learning (ML)-based methods for monitoring power system inertia. It also provides an overview of academic and industrial projects related to ML-based methods for inertia monitoring. Furthermore, the paper explores applications based on ML-based methods and inertia. Lastly, the paper briefly discusses future directions for the development of this research field.

1. Introduction

To reduce dependency on fossil fuels and curb greenhouse emissions, power systems started undergoing a systematic integration of renewable energy sources (RESs) [1]. In response to this ultimate need, traditional power plants, primarily relying on synchronous generators (SGs), are being massively replaced by converter-interfaced generation (CIG), in particular wind turbine generators (WTGs) and photovoltaic (PV) plants. Furthermore, the introduction of power electronics-based devices in both transmission and consumption aspects, such as high-voltage direct current (HVDC) transmission lines, battery energy storage systems (BESSs), and converter-connected motors, is transitioning the entire power system from its conventional mode to a new one, dominated by converters, as depicted in Fig. 1.

One of the primary challenges stemming from the system transformation is the reduction in system inertia, a concern increasingly prevalent in power systems worldwide [2]. In traditional power systems, inertia is provided predominantly by the *rotational inertia* of SGs and directly-coupled motors, which act to account for deviations in grid frequency and maintain stable frequency profiles. However, as RESs replace SGs, e.g. PV plants, BESSs, and WTG plants (Type 3 – Doubly Fed Induction Generator (DFIG) and Type 4 – Full-Scale Converter (FSC) wind turbine generators (WTGs)), the overall system inertia declines. The presence of converter-connected motors exacerbates this reduction. Consequently, the power system experiences a higher rate of change of frequency (RoCoF) and extreme frequency variations following disturbances, as shown in Fig. 2. These conditions can trigger load shedding schemes, activate other protection systems, and lead to subsequent cascading events, potentially culminating in blackouts [3]. As a result, concerns regarding frequency stability have come to the forefront, playing a critical role in ensuring reliable operation of power systems. In the past decade, numerous blackout incidents were reported and globally investigated; major events that have drawn the attention were in the United Kingdom [4], China [5], Australia [6], India [7], and

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the system split event in Europe [8]. These incidents were primarily attributed to insufficient system inertia.

In addition to the decline in system inertia, there is a fundamental shift in the nature of inertia itself. Formerly a steady-state parameter, inertia is now characterized by time-varying and spatial features. The number of online synchronously operating SGs, responsible for contributing to system inertia, fluctuates due to the intermittent nature of the RESs. In response, inertia changes dynamically with the variation of weather conditions at RES plants, including factors such as wind speed, irradiation, and temperature [9]. Furthermore, the concept of virtual inertia, supported by RESs, is subjected to variability depending on the operational limits of these resources. A prime example is observed with WTGs when employed to support system inertia. In such cases, the supported inertia must be finely adjusted to ensure the stability of WTGs, particularly in terms of their variable rotor speed, during their exploitation in the power system [10]. Moreover, the power system undergoes partitioning and separation into multiple regions facilitated by power converter-based devices like HVDC transmission lines. Consequently, SGs provide inertia within specific regions, leading to distinct frequency dynamics across various parts of the power system [11].

Due to these complex conditions, system operators face difficulties in making decisions related to dispatching and implementing rapid frequency response plans defined as Fast Frequency Control service. The challenges that have emerged underscore the importance of precise and near-real-time monitoring of system inertia in safeguarding the reliability and security of the power system. Monitoring system inertia can offer valuable reference inputs for protection and proactive control systems as the impacts of system inertia on the frequency stability is shown in Fig. 2. This approach not only boosts system stability but also improves operational efficiency. For instance, it enables more informed planning of ancillary reserves by leveraging insights into current system conditions and stability margins [12]. Research in the field of inertia monitoring is actively progressing, with a rich literature presenting various methods to address this need.

Machine learning (ML) emerges as a highly effective solution to address a number of complex problems. ML's capability to analyze vast volumes of multi-variety data allows it to uncover specific trends and patterns. These methods continuously improve their accuracy and efficiency through experience, without requiring human intervention [13]. Recently, ML-based methods have found extensive application in power system assessment, particularly through the use of wide-area monitoring systems [14]. Applications include reliability assessment [15], analysis of frequency dynamics [16,17], and resilience assessment [18].

In contrast to existing papers that review some methods for monitoring system inertia [12,19–22] and the significance of ML-based applications in power system analysis and control, this review aims to digest and summarize key insights from existing references found in the open literature as well as industry projects for monitoring system inertia based on ML-based methods. While there have been limited instances of joint applications of system inertia monitoring and ML-based algorithms in the existing literature, this paper intends to showcase these applications with the aim of inspiring further research and exploration in this field. Furthermore, it attempts to chart a path for future developments in this emerging field of engineering by identifying knowledge gaps, forthcoming requirements, and possible solutions. The primary contributions of this work are as follows:

- Review of system inertia definitions and approaches for its monitoring in both traditional and modern power systems.
- Investigation of ML-based methods used for inertia monitoring, providing an overview for researchers interested in developing new methods in this field or other related applications, e.g., frequency control.
- Comprehensive and comparative review of system inertia monitoring using ML-based methods, including an analysis of various scenarios for data collection and inertia monitoring.
- Review of academic and industrial projects related to system inertia monitoring using ML-based methods.
- Review of the limited literature on applications involving ML-based methods and associated inertia monitoring, aiming to inspire experts to further explore this cutting-edge field.
- Provision of future directions by taking into account gaps in existing published open literature, that will serve as a roadmap for further research in this field.

The paper is structured as follows: Section 2 focuses on defining system inertia, followed by a review of ML-based methods applied to system inertia monitoring in Section 3. Section 4 explores inertia monitoring methods employing ML-based techniques found in the literature, while Section 5 presents comprehensive academic and industrial projects related to system inertia monitoring using ML-based methods. Section 6 highlights applications that utilize ML-based methods and determined inertia for different types of applications like power system analysis, control, and protection. Finally, Section 7 presents the conclusion and outlines future directions.

2. Definition of system inertia

Conventionally, system inertia is defined as resistance to the speed changes of the SGs' rotors [23]. The moment of inertia (MoI) is the

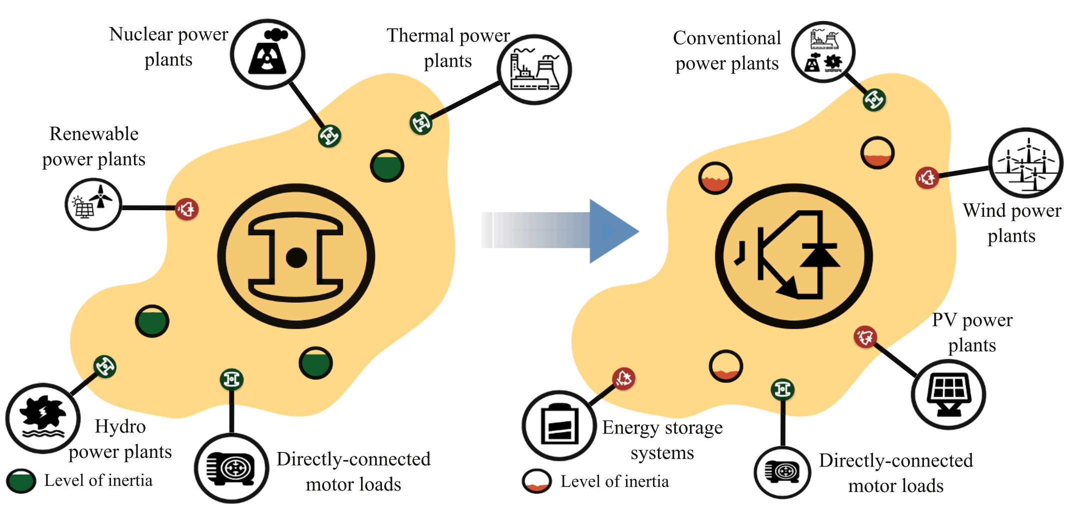

Fig. 1. Transition of the power system from a traditional one (synchronously operating generators) to a new one (converter-interfaced generation – CIG).

quantitative measure of rotational inertia for a rigid body rotating around an axis. Let's consider a cylinder with the mass of m rotating around the x-axis as shown in Fig. 3. The MoI of this cylinder according to the x-axis is defined as follows:

$$J_{cylinder} = \frac{1}{2}mr^2 \tag{1}$$

where m and r are the mass in kg and radius in m of the cylinder. $J_{cylinder}$ is the MoI of the cylinder expressed in kgm^2. To determine the MoI of SG's rotor with the multi-mass objects that are rotating, firstly, the MoI of each rotating component of the rotor including core packs, copper wire, insulations, wedges, bearings and fan is calculated concerning its center of gravity [24]. Then, these MoIs are modified according to the distance from their centers of gravity to the main rotor centerline by using the parallel axis theorem [25]. Finally, the MoI of SG's rotor is the sum of the MoI of all rotating components as,

$$J = \sum_i (J_{c_i} + m_{c_i} {}^* r_{c_i}) \tag{2}$$

J is the MoI of SG's rotor and J_{c_i} is the MoI of i-th rotating component due to its center of gravity. m_{c_i} is the mass of i-th rotating component and r_{c_i} is the distance between the centerline of the rotor and the center point of i-th rotating component. The kinetic energy stored in the rotating masses of the SG's rotor is defined as,

$$E_k = \frac{1}{2}J{\omega_m}^2 \tag{3}$$

E_k is the kinetic energy of the SG's rotor in MVAs; ω_m is the angular velocity of SG in rad/s. When a torque mismatch occurs for torques acting on the rotor of a SG, the SG naturally releases or absorbs its kinetic energy stored in the rotating masses. This process is called inertial response and could be described mathematically by the swing equation of the SG in terms of mechanical and electrical powers [26],

$$\Delta P_{m,i} - \Delta P_{e,i} = 2H_i \frac{d}{dt}(\Delta\omega_{m,i}) \tag{4}$$

$\Delta\omega_{m,i}$ is the deviation of the angular velocity of i-th SG from nominal velocity in per unit (p.u.). $\Delta P_{m,i}$ is the change of mechanical power input of i-th SG in p.u. corresponding to the power supplied by it. $\Delta P_{e,i}$ is the change of electrical power output of i-th SG in p.u. related to the power demand from the load. If the damping factor of frequency-dependent loads is included, the aforementioned swing equation is modified according to [26]:

$$\Delta P_{m,i} - (\Delta P_{L,i} + D_i \Delta\omega_{m,i}) = 2H_i \frac{d}{dt}(\Delta\omega_{m,i}) \tag{5}$$

D_i is the damping factor and $\Delta P_{L,i}$ is the power change of frequency-independent loads in p.u. H_i is the inertia constant of i-th SG in seconds and is defined as [26],

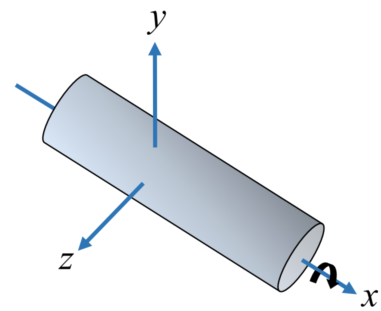

Fig. 3. Cylinder rotating around the x-axis.

$$H_i = \frac{E_{k_i}}{S_{r_i}} = \frac{\frac{1}{2}J_i{\omega_{m_0,i}}^2}{S_{r_i}} \tag{6}$$

E_{k_i}, S_{r_i}, $\omega_{m_0,i}$, and J_i are the kinetic energy in MVAs, the rated apparent power (base power) in MVA, the rated rotor speed, and the rotor's MoI of i-th SG, respectively. The amount of kinetic energy released or absorbed by each SG depends on the MoI and the speed $\omega_{m_0,i}$. Consequently, the rotor speed and, by extension, the system frequency, will vary in proportion to the MoI. In power system studies, the inertia constant, H, is commonly used to express the system's ability to resist changes in rotational speed. The inertia constant has to be understood as a time constant. The physical significance of H lies in the fact that when the input mechanical power of an SG is zero, and SG injects nominal electrical power solely by releasing its stored kinetic energy, the rotor speed of the SG will reach zero after $2H$ seconds [26]. In other words, within this time frame, the SG expends all of its stored kinetic energy to compensate for the active power imbalance, equal to its nominal power, without any mechanical power input. When equivalenting the entire electrical power system with a single generator, it is possible to define the system inertia constant, H_{sys}, and frequency of the equivalent inertia center, f_{CoI}, [27,28]. This can be realized by summing up the H_i values of all individual SGs and considering their measured frequencies, power system inertia and the frequency of the center of inertia can be expressed as:

$$H_{sys} = \frac{\sum_{i=1}^{N_{SG}} S_{r_i} H_i}{\sum_{i=1}^{N_{SG}} S_{r_i}} \tag{7}$$

$$f_{CoI} = \frac{\sum_{i=1}^{N_{SG}} H_i f_i}{\sum_{i=1}^{N_{SG}} H_i} \tag{8}$$

where H_{sys} is the system inertia constant in seconds and f_{CoI} is the frequency of the center of inertia in Hz. f_i is the frequency of the i-th SG and N_{SG} is the number of online SGs. Similarly, the aggregated swing

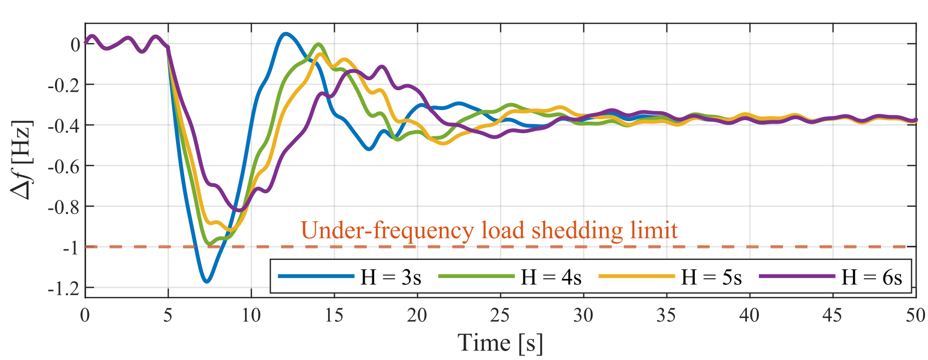

Fig. 2. Effects of system inertia decline on the frequency deviations following a disturbance event.

equation can be approximated by ignoring the damping factor in the initial moments of disturbance as follows:

$$\frac{2H_{sys}}{f_n} \times \frac{df_{CoI}}{dt} = \frac{P_{generation} - P_{load}}{S_B} = \frac{\Delta P}{S_B} \tag{9}$$

where $P_{generation}$, P_{load}, and ΔP are the aggregated generated power, power demand, and active power mismatch in MVA, respectively. f_n is the nominal frequency in Hz and S_B is the base power in MVA. The system RoCoF is obtained from (9):

$$RoCoF = \frac{df_{CoI}}{dt} = \frac{\Delta P \times f_n}{2 \times H_{sys} \times S_B} \tag{10}$$

It is evident from (10) that the frequency dynamics of the power system dominated by SGs highly depend on the system inertia. In modern power systems penetrated by high shares of RESs, system inertia is provided from two kinds of sources: rotational inertia resulting from synchronous machines and virtual inertia supported by RESs [29],

$$H_{sys} = \frac{\sum_{i=1}^{N_{SG}} S_{r_i} H_i + \sum_{j=1}^{N_{VI}} S_{VI_j} H_{VI_j}}{S_B} \tag{11}$$

S_{VI_j} and H_{VI_j} are the nominal apparent power and virtual inertia of j-th RES contributing to the virtual inertia, respectively. N_{VI} is the number of RESs supporting the virtual inertia. According to this equation, the system inertia is not determined by the number of online SGs but is obtained by considering the frequency variations and active power mismatch between generation and consumption based on (9).

3. Ml-based methods applied to inertia monitoring

To introduce the ML-based methods employed in system inertia monitoring, an overview of common terminologies is made. This overview outlines the core of ML-based problems, and explain the structure of ML-based methods. The fundamental objective behind developing an ML-based method is to make predictions or estimations based on the input features or measurements. In our case, this estimation capacity pertains to determining the system inertia.

To fulfill this objective, ML-based methods are trained using a dataset. Depending on the nature of the target and training data, ML-based methodologies can be broadly classified into three main categories: supervised learning, unsupervised learning, and reinforcement learning (RL) [30]. In supervised learning, model is trained iteratively, relying on labeled datasets. Model's primary goal is to minimize the difference between its estimations and the provided correct answers. Common ML models for supervised learning include decision trees [31], neural networks [32,33], linear regression [34], nearest neighbor [35], and support vector machines [36,37]. In our context, most of the system inertia monitoring methods based on ML-based methods fall under supervised learning, with the system inertia value serving as the label. In contrast, unsupervised learning operates without labeled data. Methods in unsupervised learning autonomously explore and discern inherent structure within unlabeled datasets, uncovering patterns, groupings, or relationships within the data. The K-means algorithm [38], principal component analysis [39], and hidden Markov models [40] are the most famous models for unsupervised learning.

RL represents a distinct learning approach, setting itself apart from the two previously mentioned methods. RL focuses on how an agent makes sequential decisions within an uncertain environment to maximize cumulative rewards. Its applications in power system operation and control have recently garnered significant attention [41,42]. Given the advanced decision-making capabilities inherent in RL, researchers have integrated it with the perceptual prowess of Deep Learning (DL), culminating in the Deep Reinforcement Learning (DRL) framework [43]. The various advantages of DRL techniques, including a high-complexity processing system, data-driven and model-free approaches, and adaptability, have led to endeavors in recent years to apply DRL in wind farm control tasks [44,45], including wind farm power regulation and tracking [46,47]. Moreover, DRL finds applications in diverse areas such as power market trading [48], frequency response [49], demand response [50], and autonomous voltage control [51].

Fig. 4 illustrates the typical structure involved in constructing an ML-based method, showcasing the different stages of dataset building, data preprocessing, model training, and evaluation. The initial step in building an ML-based method is the creation of a robust dataset. In cases where historical data may be scarce, simulations are conducted to generate a training dataset. Striking the right balance in the dataset's representation is pivotal for achieving a reliable and practical ML-based method.

After constructing a dataset, the next important step is the data preprocessing before it is utilized by a learning algorithm. During this stage, feature engineering plays a pivotal role, encompassing both feature extraction and feature selection techniques. Feature extraction involves transforming the data to represent it in a more meaningful and compact manner. This transformation serves to enhance the model's ability to capture essential patterns within the data while reducing its dimensionality [52]. Feature selection algorithms such as wrapper and genetic algorithms are employed to identify and retain the most relevant and informative features from the dataset [53]. Focusing on data key aspects, feature selection simplifies the model, mitigates the risk of overfitting, and ultimately leads to more accurate and efficient learning.

Numerous learning algorithms are available for constructing ML-based methods, and the choice of the most suitable one depends on various factors like the type of dataset and the specific requirements of the task. Typically, the training takes place offline, but methods may also be updated online as new data becomes available. Given the diverse landscape of the learning algorithms, a prudent approach involves experimenting with different learning algorithms and assessing their performance against the dataset.

The final stage of ML-based method construction is model validation, a crucial step in the development of any ML-based system. By testing the model on unseen data, it verifies the generalization capability of the established model. With these considerations, the subsequent sections will delve into the specific models applied to ML-based system inertia monitoring methods, paying attention to their methodologies and applications.

3.1. Artificial neural network

In the various ML-based techniques, Artificial Neural Network (ANN), inspired by the intricate workings of the human brain, has garnered significant attention across a wide array of research domains [54]. An ANN is a computational model composed of interconnected nodes (neurons) arranged in layers: an input layer, one or more hidden layers, and an output layer. This layered architecture is depicted in Fig. 5. Each connection between nodes has an associated weight that is adjusted during training. The network learns by optimizing these weights to minimize the difference between predicted and actual outputs. The main advantages of ANN are including versatility, learning capability, non-linearity, feature extraction, and scalability. While, the drawbacks of this ML model consist of data requirements, computational resources, interpretability, overfitting, and hyper-parameter tuning. ANN is particularly suitable for static data scenarios, where the same conditions are repeatable, such as in pattern recognition [55], classification [56,57], forecasting [58,59], and similar tasks.

3.2. Recurrent Neural Network

Recurrent Neural Network (RNN) is a specialized type of neural networks designed to handle time series data or sequences, which can originate from various sources such as text, speech, or video. Fig. 6 provides an overview of the inner workings of an RNN unit, which is

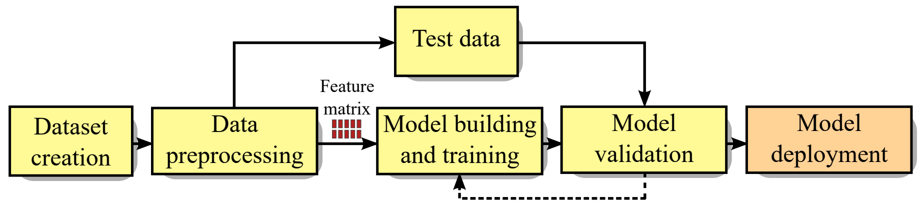

Fig. 4. General structure of constructing an ML-based method.

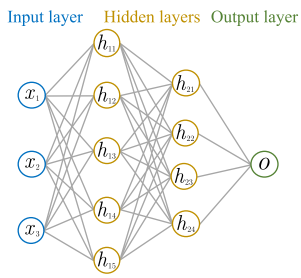

Fig. 5. Typical structure of MLP.

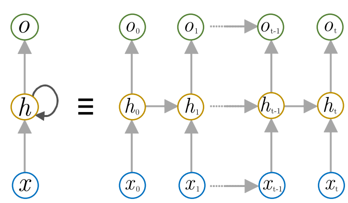

Fig. 6. Structure of an RNN unit.

central to its sequential processing. One of the key attributes that sets RNNs apart is their ability to incorporate a form of "memory", allowing them to retain and utilize information from prior inputs, which influences the processing of future time steps to generate subsequent outputs within a sequence [60]. The main advantages of RNN are including sequential data handling, temporal dependencies, variable input/output length, and parameter sharing. However, the drawbacks of this ML model consist of vanishing gradients, training difficulty, limited memory, computational cost, and complexity. To address the vanishing gradient problem, the Long Short-Term Memory (LSTM) network has emerged as a remarkable RNN architecture. LSTMs are designed specifically to overcome this challenge, enabling the network to capture and utilize information over long sequences effectively [61]. The impact of LSTM-based networks has been profound across various fields, including language modeling [62], speech-to-text transcription [63], machine translation [64], and other applications.

3.3. *Convolutional neural network*

Convolutional Neural Network (CNN) is a widely used class of neural networks, especially for spatial patterns analysis. CNNs are specifically designed to learn spatial features within the data, such as edges, corners, textures, or more complex shapes, that are essential for classifying or quantifying targets [65]. A typical CNN architecture, as shown in Fig. 7, consists of several key layers, including convolutional layer for extracting feature map, pooling for down-sampling feature maps, flatten layer for reshaping the data into one-dimensional array, and fully connected layer for classification. The main advantages of CNN are including automatic feature extraction, spatial hierarchy, parameter sharing, and scalability. While, the drawbacks of this ML model consist of computational resources, interpretability, overfitting, design complexity, lack of interpretability, and need for large datasets. CNNs find their applications in various real-world problems, including but not limited to image recognition [66,67], natural language processing [68], video analysis [69], anomaly detection [70], drug discovery and health risk assessment [71], and recommender systems [72]. There are several modified architectures of CNNs, some of which have been adapted for monitoring system inertia. These models support the core principles of CNNs while incorporating specific modifications to address the unique challenges of system inertia monitoring.

3.3.1. *Graph Convolutional network*

Graph Convolutional Network (GCN) is a combined architecture of CNNs and graph neural networks (GNNs) models specially designed for processing and making inferences on graph-structured data, where nodes represent entities and edges represent relationships between them [73]. One of the key strengths of GCNs is their ability to aggregate node information from neighbourhoods in a convolutional manner. This enables the model to learn and represent complex relationships between nodes within the graph. GCNs have found applications in various domains, including making recommendations in the recommender systems [74,75], and forecasting traffic conditions [76]. In the context of power systems, which consist of interconnected generators and loads, GCNs are applied to understand the graph structure of the power systems, comprising nodes (buses) and edges (branches) [77,78]. Another advanced model of GNNs used in the system inertia monitoring is Graph Attention Networks (GATs). GATs allocate different levels of attention to neighbouring nodes during information diffusion, learning the

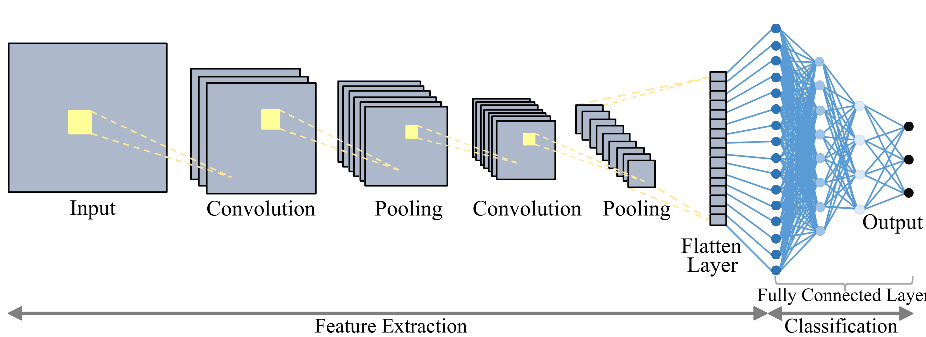

Fig. 7. Typical CNN architecture.

importance of each node in a graph [79]. By utilizing attention mechanisms, GATs effectively capture intricate relationships and spatial dependencies, improving their performance in tasks like node classification and link prediction.

3.3.2. Residual neural network

Residual neural Network (ResNet) represents a significant advancement in CNN-based architectures, addressing the vanishing gradient problem that tends to occur in deep networks with many layers [80]. ResNet introduces a "shortcut connections" or "skip connections" to facilitate the training of very deep networks, allowing the gradients to flow more effectively through the network without vanishing or exploding. The ability to train very deep networks with ResNet has led to improved accuracy on various computer vision tasks, such as image classification [81], object detection [82], and segmentation [83].

3.3.3. Long-Term Recurrent Convolutional network

Long-term Recurrent Convolutional Network (LRCN) is a hybrid neural network architecture that combines the strengths of CNN and LSTM networks [84] to integrate spatial and temporal learning. The strength of the LRCN lies in its ability to integrate the spatial features extracted by the CNN with the temporal context captured by the LSTM, making it particularly well-suited for applications like activity recognition [85], image captioning [86], and video description.

3.4. Physics-Informed neural network

Physics-Informed Neural Network (PINN) represents a novel approach to solving problems with limited data, particularly when dealing with noisy experimental measurements. These networks are designed to seamlessly integrate information from both data measurements and the governing physical laws of the problem [87]. PINNs do this by embedding Partial Differential Equations (PDEs) into the loss function of a neural network using automatic differentiation. Fig. 8 shows the general structure of a PINN. The capability of PINN in addressing the complex problems that involve physical laws and limited data has led to gain significant attention and exploration in various scientific and engineering disciplines due to its potential advantages, including hydrology, chemistry, materials science, earth systems, hydromechanics, and more [88–91] as well as power system studies [92,93].

3.5. Federated learning

Federated Learning (FL) represents a significant shift in the field of ML, transitioning from a centralized and resource-intensive approach to a distributed paradigm that leverages the power of numerous distributed computing resources [94]. This approach not only offers advantages in terms of data privacy but also reduces network overhead by transmitting only model updates rather than raw data [95]. FL, as illustrated in Fig. 9, involves two main entities: clients and a central server. Clients typically represent individual devices or data sources, while the central server coordinates the learning process. In recent years, FL has demonstrated successful applications across various industries, particularly those related to the Internet of Things and edge computing, where privacy-preserving ML-based methods are crucial [96]. Also, it is gaining interest in high-dimensional organizations, energy systems, and smart grids with distributed data sources, where data privacy and security are paramount [97].

3.6. Multivariate random Forest regression

Multivariate Random Forest Regression (MRFR) is a powerful supervised ML-based algorithm that leverages the principle of random forests for regression tasks. Fig. 10 shows the typical structure of the MRFR algorithm. MRFR is an ensemble learning technique that builds multiple base models (regression trees) and aggregates their predictions to make accurate and robust predictions [98]. It has been successfully applied in various domains, including disease prediction [99], mobile networks [100], localization systems [101], and parameter assessment and estimation [102]. Table 1 summarize the main features, variants, pros and cons of ML models used for ML-based system inertia monitoring methods.

4. Ml-based methods for inertia monitoring

Implementation of ML-based methods for inertia monitoring in power systems involves several stages. These stages, illustrated in the typical process depicted in Fig. 11, include data acquisition, feature engineering, model training and validation, and the online deployment of the trained model. In the context of data acquisition and the scenarios under which data is collected, inertia monitoring methods based on ML-based algorithms can be broadly classified into three main methods: contingency operation-, normal operation-, and perturbation-based approaches. These methods are discussed here below.

4.1. Contingency Operation-Based methods

In these methods, system's reactions during the events are analyzed by an ML-based algorithm to monitor the system inertia. To train and validate the ML-based method, the size and type of disturbances, as well as the system inertia, are varied, and a variety of measurements are collected. The extracted inertia information can be used for designing load shedding plans [103] and fast frequency control schemes for RESs [104,105].

The paper in [106] presents an ANN-based method for inertia monitoring using measured system frequency signal as the input. This approach involves discretizing the frequency signal and feeding each

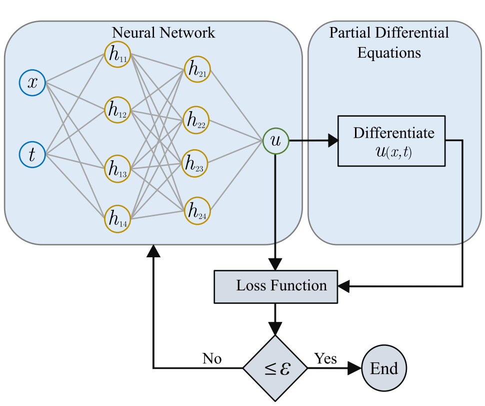

Fig. 8. General structure of a PINN.

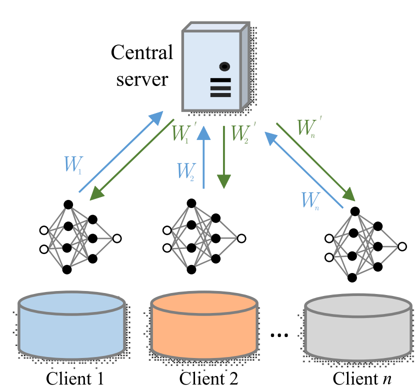

Fig. 9. Diagram of FL structure.

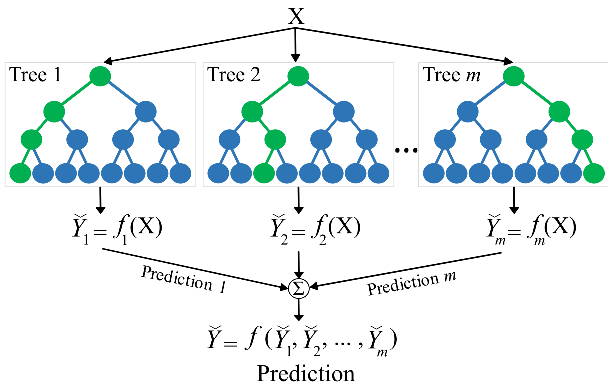

Fig. 10. Typical architecture of the MRFR algorithm.

Table 1
ML models used for ML-based system inertia monitoring methods.

Model	Main features	Variants	Pros/Cons
ANN	Computational model composed of interconnected neurons arranged in layers.		+ Versatility; learning capability; feature extraction; non-linearity; scalability. − Data requirements; interpretability; computational resources; overfitting; hyper-parameter tuning.
RNN	Well-suited for tasks where data is sequential or time-dependent.	LSTM	+ Sequential data handling; temporal dependencies; variable input/output length; parameter sharing. − Vanishing gradients; training difficulty; limited memory; computational cost; complexity.
CNN	Effective for processing the grid-like data, such as images.	GCN ResNet LRCN	+ Automatic feature extraction; spatial hierarchy; parameter sharing; scalability. − Computational resources; design complexity; interpretability; overfitting; lack of interpretability; need for large datasets.
PINN	Incorporation of governing equations of a physical system in ML model.		+ Direct integration of physics; data efficiency; flexibility; generalization; reduced computational cost. − Training complexity; limited to well-defined physics; convergence issues; choice of network architecture; accuracy of physical models.
FL	To allow multiple decentralized devices to collaboratively train a model; Keeping the data localized on each device.		+ Data privacy and security; reduced data transfer; scalability; adaptability; regulatory compliance − Communication overhead in large models; computational resource requirements; process of heterogeneous data; model aggregation challenges; inconsistent updates;
MRFR	An ensemble learning technique; To build multiple decision trees and aggregates their predictions.		+ Handling multiple targets; robustness; feature importance; non-linearity; no need for scaling. − Computational complexity; model interpretability; overhead of multiple targets; memory usage; hyper-parameter tuning.

frequency sample to the individual neurons in the input layer of the ANN. The dataset used for training and validation is generated by varying the system inertia and event size (both positive and negative). While this method was initially proposed and verified for a small power system, its practical applicability to larger-scale power grids was limited due to the system's size and complexity.

To address this limitation and make the inertia monitoring method more applicable to realistic conditions, researchers used the IEEE 39-bus test system [107–110]. The frequency signals from all buses in the IEEE 39-bus test system are measured [107] and these measurements are taken during various generator and load events, allowing for a diverse dataset. One crucial aspect highlighted in [107] is the careful selection of f_{COI} for achieving high accuracy in inertia monitoring. Both f_{COI} and its corresponding RoCoF are calculated from the measured frequency signals to train the ResNet model.

Frequency signal and active power imbalance are chosen as input features to train and test the ML-based methods [108,109]. Considering load and generator disturbances, a one-dimensional CNN is applied to establish the relation between f_{COI} and system inertia [108]. Since LSTM is a powerful tool analyze the data sequences, it is implemented in [109] by considering the load events. Because the active power mismatch is prevalently unknown, the selection of this parameter as the input feature of the model is a challenge which is highlighted in these two methods. Besides, the use of local frequency signals instead of f_{COI} may not capture the system-wide behavior accurately in [109].

The method proposed in [110] addresses the challenge in monitoring the regional distribution of system inertia in power systems with increasing shares of RESs. The primary goal of this method is to monitor the regional distribution of system inertia. Generators with similar frequency response characteristics are clustered using the K-means algorithm. The input features of the model, which is LSTM, are a wide range of data, including the measured signals of frequency of SGs' buses, active and reactive powers of SGs and loads, and voltage and phase angles of all buses. This comprehensive set of features allows the model to capture the spatial distribution of inertia by considering the data from various sources in the power system. However, clustering the generators accurately based on the frequency response characteristics can be challenging as the accuracy of the clustering process affects the model's performance. Additionally, the integration of RESs and their inherent uncertainty can introduce complexities that may need further consideration.

To optimize the computation time for monitoring the system inertia using ML-based methods, an autoencoder is employed in [111] to compress the large volume of data gathered from synchro-phasors through unsupervised learning. In this ML-based approach, locally measured signals of system frequency and RoCoF from selected buses are fed into the autoencoder. This process maps the extensive frequency data to a small, and finite number of abstract features—specifically, five attributes. These features are then used as inputs for an ANN to monitor the system inertia. The limitations of this proposed method include the use of a simple single-machine model of the power system for collecting the training dataset, the exclusion of noise in frequency measurements, and the lack of consideration for the participation of RESs in virtual inertia. Additionally, the performance of this method in large-scale power systems is highly dependent on the observability of the system, as provided by the selected buses for local measurements of the system frequency.

The existing contingency-based methods for inertia monitoring have advantages, however, they present certain disadvantages, highlighted as: 1) these methods do not account for the effects of virtual inertia provided by RESs. Virtual inertia provided by RESs can significantly influence the total equivalent system inertia. Ignoring this aspect may lead to incomplete assessments of the power system's inertia status. 2) the aforementioned methods do not incorporate measurement noise into the dataset used for training and validating the ML-based method. For practical scenarios, measurement noise is a common concern in the

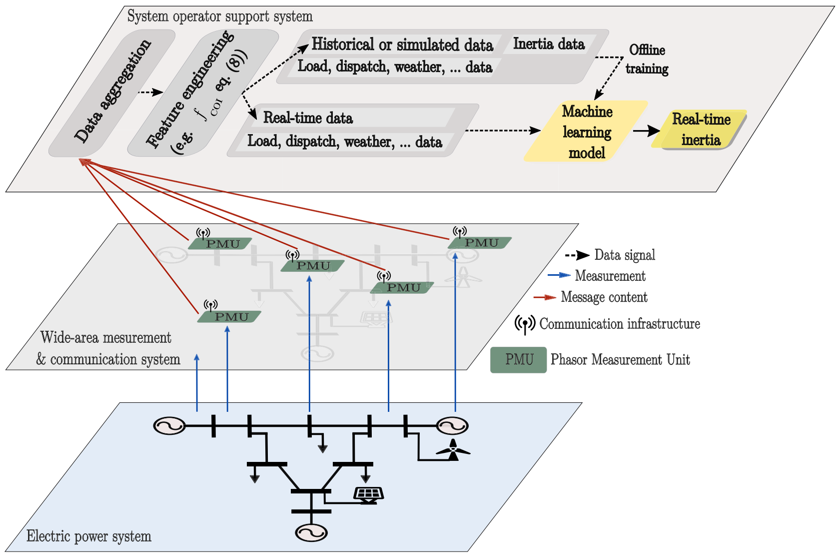

Fig. 11. Typical process of system inertia monitoring based on ML-based method.

power system's data collection. Ignoring the measurement noise in the dataset may affect the accuracy and robustness of inertia monitoring. Table 2 summarizes the properties and relative comparisons of contingency operation-based methods.

4.2. Normal Operation-Based methods

Continuously updating the status of system inertia in real- or near-real-time is essential for power system operators to ensure grid stability and manage the dynamics of modern power systems. Monitoring system inertia during normal operation, as opposed to relying solely on contingency-based methods, provides a valuable alternative. The primary objective of these approaches is to monitor system inertia during normal operation using ML-based methods. The data for constructing the ML-based method can be obtained from the historical data of the actual power systems or simulation models of the power system. Other useful data sources can also be incorporated to enhance the accuracy of the ML-based method.

For accurate monitoring the time-varying inertia using ML-based methods, two conditions should be met: 1) The implemented ML model should be capable of processing temporal data; and 2) The training dataset, including input features and output inertia, must adequately represent the time-varying operational conditions of the power system. For example, inertia data, which serves as label information, can be associated with selected input features measured in the real power system over a period (e.g., one or two years) to develop the ML-based inertia monitoring method. In this scenario, the time-varying tracking of the ML-based inertia monitoring method depends on the reporting interval of the inertia data. The methods described in [112,113] integrate various data sources, including real-time measurements, data from transmission system operators and the reliability coordinator, and meteorological data, to develop an ML-based method for continuous inertia monitoring. The MRFR method is selected for this purpose due to its capability to handle multiple data sources and provide robust predictions. Frequency measurements from twenty Phasor Measurement Units (PMUs) spread across the U.S. Western Electricity Coordinating Council (WECC) system are collected. The minimum volume enclosing ellipsoid method [114] is then used to construct an ellipsoid from the time-series frequency information, which helps extract informative features that capture the correlation between time-varying system inertia and frequency. Four key parameters derived from the constructed ellipsoid are chosen as descriptive features for inertia monitoring: volume, center vectors, projections of the longest semi-axis along each dimension, and eccentricity. In addition to these graphical parameters, load profiles from transmission system operators and actual weather data from multiple U.S. cities are collected. System inertia data obtained from the reliability coordinator serves as the label for training the ML-based method. The time-varying tracking capability of this ML-based inertia monitoring method depends on the reporting interval of the inertia data provided by the reliability coordinator, which is ten minutes in this case. Given the small reporting interval, the ML-based method can monitor inertia in shorter time windows. This method enables monitoring of the system's available kinetic energy and system inertia on both yearly and daily bases, offering insights into long-term trends and daily variations.

Another approach to harnessing ML-based methods for monitoring system inertia is demonstrated in [115]. This approach employs a multivariate mixture modeling technique that combines non-Gaussian distributions with Markov chains to capture the complex stochastic and specific temporal dependencies between system frequency and inertia. Continuous monitoring of power system inertia is achieved online using only steady-state system frequency as input. Frequency measurements are collected from three Phasor Measurement Units (PMUs) installed at different universities in the United Kingdom, capturing continuous frequency variations over a two-year period. System inertia data, which serves as the target variable for training the ML-based method, is prepared by gathering generation dispatch information from the transmission operator. During the deployment stage, the ML-based method is periodically recalibrated using the generation dispatch information, which enhances the flexibility and accuracy of the monitoring. Similar to the methods proposed in [112,113], the time-varying tracking capability of this ML-based inertia monitoring method depends on the reporting interval of the inertia data provided by the generation dispatch information. An important consideration is the need for a large historical dataset for training, which may pose challenges if such data is not readily available.

The authors in [116] focus on monitoring system-, regional-, and bus-level inertias using an ANN-based method providing inter-area modal information. Frequency measurements are collected from all buses in the IEEE 118-bus system, divided into three regions based on the graph theory [117]. The modal information of the system is determined, including the first four modes of the frequency for each bus. The dataset is created by varying the inertia of SGs and direct-connected motors, which is used for training and testing the ANN-based method. The method provides the monitoring of system-, regional-, and bus-level inertias. However, the results indicate the limited accuracy of

Table 2
Comparison of contingency operation-based inertia monitoring.

Ref.	Type of monitoring	ML model	System type and considerations	Input features	Pros/Cons
[106]	System inertia*	ANN	Two-bus test system without any controller;	Discretized frequency signal	– Simple power system; – Local frequency measurement; – Ignoring noise in measurements; – Ignoring the participation of RESs in virtual inertia;
[107]	System inertia	ResNet	IEEE 39-bus system model; Generator and load events;	f_{COI} and its corresponding RoCoF	+ Considering f_{COI}; – Ignoring noise in measurements; – Ignoring the participation of RESs in virtual inertia;
[108]	System inertia	CNN	IEEE 39-bus system model; Generator and load events;	f_{COI}; disturbance size;	+ Considering f_{COI}; – Selection of disturbance size as the input feature; – Ignoring noise in measurements; – Ignoring the participation of RESs in virtual inertia;
[109]	System inertia	LSTM	IEEE 39-bus system model; Load events;	Frequency signal; disturbance size;	– Local frequency measurement; – Selection of disturbance size as the input feature;
[110]	Regional inertia**	LSTM	IEEE 39-bus system model; Clustering the generators in multiple regions;	Frequency signal of generators; active and reactive power signal of generators and loads; voltage and phase signals of all busses;	– Ignoring the participation of RESs in virtual inertia; – Ignoring noise in measurements;
[111]	System inertia	ANN	Single-machine model;	Local measured frequency; RoCoF;	+ computation-efficient method; – Simple power system; – Ignoring the participation of RESs in virtual inertia; – Ignoring noise in measurements; – Challenge in local measurements;

* System inertia refers to the equivalent inertia constant based on (7).
** Regional inertia refers to the equivalent inertia of a region with the busses which have the frequency responses with the same trend.

monitoring bus-level inertia. It is important to note the limitations of this method as this approach is primarily designed for large-scale power systems with SGs and may not be sufficiently suitable for systems with a high penetration of RESs.

In [118], the authors present the development of an inertia monitoring approach based on an MLP-based method. This method utilizes the measurements obtained from the power flow analysis in monitoring system inertia. Input features for the MLP-based method are chosen based on the Pearson correlation coefficient analysis [119]. The selected variables include the total active power generation from all SGs and all converter-interfaced generators, the total power of induction motor loads directly coupled to the system, and the loading of transmission lines. The MLP-based method is trained and validated using the selected input features and the corresponding inertia data obtained from the IEEE 9-bus system model. In the validation stage, the performance of the trained MLP-based inertia monitor is validated by implementing Hardware-In-the-Loop (HIL) testing. One notable limitation of this approach is its validation for a small-scale power system.

A CNN-based inertia monitoring method that focuses on extracting area-level inertia using the voltage signals from the selected buses is proposed in [120]. In this method, a variable called "momentum" (M) is monitored instead of inertia constant by using:

$$M = 2\sum_{i=1}^{N_{SG}} \frac{H_i{}^{*}S_{r_i}}{f_n} \tag{12}$$

The reason for using momentum for monitoring is that it is an incremental variable; when a component with inertia is connected to the grid, the momentum increases. Unlike the inertia constant, which may remain unchanged if the inertia of the new component matches the center of inertia (the average weighted inertia of the system), momentum effectively captures changes in inertia as components are connected or disconnected. To validate this approach, synthetic data is generated by simulating the IEEE 39-bus benchmark system, which is divided into four areas [121]. The test system is modified to model variations in load power more realistically. Time-varying voltage measurements from a limited number of buses are selected, and their harmonics are used as input features for the CNN-based method to monitor momentum in the selected area. By varying the inertia of SGs in each area of the test system and measuring the voltages at the selected buses, a training dataset is prepared to establish the ML-based inertia monitoring method. This developed method can continuously monitor the time-varying system inertia.

The study described in [122] presents a method for monitoring the equivalent system inertia, which includes the inertia of SGs and the virtual inertia supported by the virtual synchronous generator (VSG) operation of RESs at the distribution level. Additionally, it considers the damping effects of RESs. The study takes into account various RESs, including WTG and PV farms, and BESSs equipped with the VSG control. These sources have technical limitations, such as dead band, delay, and saturation, which impact their behavior and interaction with the grid. The VSG block diagram is illustrated in Fig. 12, highlighting the nonlinear properties. H_{VSG} and D_{VSG} are the virtual inertia and damping of each source, respectively. PINN based on RNN is proposed to monitor the equivalent system inertia while considering the VSG control of RESs. The monitoring includes the inertia of SGs, the virtual inertia provided by VSG operation in RESs (H_{VSG}), and the damping effect (D_{VSG}). The validation process involves the collection of data from the European medium voltage distribution system with stochastic load variations, enhancing its applicability to practical scenarios. Input features for the PINN-based method encompass the frequency signals of SG, the active powers of SG, WTG farms, and BESSs. It also seeks to establish connections between the weather-related data and virtual inertia of RESs, recognizing the role of environmental conditions in grid behavior.

The research discussed in [123] addresses the monitoring of regional inertia by utilizing the frequency and power data from PMUs. This method determines the inertia constant for each region based on the

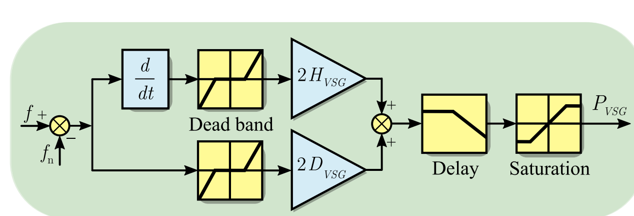

Fig. 12. VSG block diagram with nonlinear properties.

Table 3
Comparison of normal operation-based inertia monitoring.

Ref.	Type of monitoring	ML model	System type and considerations	Input features	Pros/Cons
[112,113]	Yearly and daily system inertia	MRFR	U.S. WECC system	Four constructed ellipsoid parameters; inertia data; load profile; weather data;	+ Monitoring system inertia in the real power system; − Availability of real-time inertia data and load profile are challenging;
[115]	Time-varying system inertia	Markov chain	U.K. power system	Frequency signals	+ Monitoring system inertia in the real power system; − Requiring a large historical data;
[116]	System inertia; Regional inertia; Bus inertia;	ANN	IEEE 118-bus system model; Consideration of Inertia of generators and directly-connected motors;	Modal information of frequency signals;	+ Monitoring of three levels of inertia; − Limited accuracy especially at bus level; − Monitoring of inertia for power system with only SGs;
[118]	System inertia	ANN	IEEE 9-bus system model; SGs are replaced by WPP; Dynamic loads are considered;	Active power from all SGs; Active power produced by all CIGs; Total induction motor loads;	+ Verification of method by the experiments; − Small power system;
[120]	Area-level momentum	CNN	IEEE 39-bus system model;	Harmonics of bus voltages;	− Determining the areas and busses for measurement is challenging; − Ignoring noise in measurements;
[122]	Equivalent inertia and damping coefficient of VSG operation of RESs	PINN	European medium voltage distribution system; Stochastic variations of load; VSG operation of RESs associated with nonlinearities;	Frequency signal of SG; Active powers of SG, WTG farm, and BESS; Irradiation and wind speed data;	+ Monitoring of Equivalent inertia including the inertia of SGs and virtual inertia of SGs; + Monitoring of VSG parameter of RESs; − Ignoring noise in measurements;
[123]	Regional available kinetic energy	RL	IEEE 39-bus system model;	Frequency and power of all generator's busses;	+ Do not need any offline training; − Ignoring the penetrations of RESs and their frequency contributions;

electrical power and kinetic energy variations, assuming constant mechanical power within the frequency extremums during normal operations. To address the inaccuracies resulting from the variations in the mechanical power of SGs, an RL algorithm is employed to detect the changes in the mechanical power, thus eliminating invalid inertia values. It is worth noting that the main limitation of this method is its poor performance for the power systems with the high penetration of RESs.

It is a point of concern that system inertia monitoring during normal operation may not provide accurate information for different contingencies, where system inertia can differ from its steady-state value. It is exemplified when transmission line or transformer outages occur and power system is separated into several areas with different inertias apart from the steady-state inertia. In this way, for different contingency scenarios, it is essential to determine system inertia accurately so that the dynamic response of the power system during disturbances is correctly estimated. The monitoring plays a critical role in the decision-making process for the system operators, which is essential in maintaining grid stability and undertaking the corrective actions. Additionally, the noise measurement is crucial for the accuracy of inertia monitoring methods. Table 3 summarizes and compares the specifications of normal operation-based methods.

4.3. Perturbation-Based methods

Utilizing the excitation signals generated by the power electronics-interfaced sources to monitor system inertia is an intriguing approach [124]. It involves perturbing the system in a controlled way without compromising system stability, measuring the resulting output responses, and then using ML-based methods to identify system inertia. This approach can be particularly valuable for monitoring inertia's status under controlled conditions and studying the system's response due to different disturbances.

In [125], a method developed for monitoring system inertia of a single-machine power system consisting of a WTG and a PV system provides valuable insights into inertia monitoring under specific conditions. The size of the perturbation and the initial RoCoF are selected to train and test the ML-based method. Since the input features are static during the same iterative conditions, a feedforward ANN has been selected as model. To calculate the initial RoCoF, the system frequency is measured, and the initial RoCoF is calculated by the derivative of the fifth order polynomial function fitted with measured frequency data [126] as follows:

$$\frac{\Delta f}{f_n} = A^*t^5 + B^*t^4 + C^*t^3 + D^*t^2 + E^*t + F \tag{13}$$

$$InitialRoCoF = \left.\frac{d(\Delta f/f_n)}{dt}\right|_{t=0} \tag{14}$$

One notable advantage of this method is its ability to monitor the inertia both during steady-state and disturbance conditions. By including data from both scenarios in the training dataset, the ML-based method can potentially provide a useful inertia monitoring for various operational states. However, the results obtained by this simplified model may not directly translate to large-scale power systems with complex interconnected components. Furthermore, the method does not explicitly consider the measurement noise in the training dataset.

To monitor the time-varying inertia based on perturbation-based methods, the probing signal is continuously and periodically injected into the power system. The effect of this signal injection on the power system, which experiences varying operational conditions in terms of system inertia at different moments, allows for temporal inertia monitoring by measuring the selected variables and feeding them into the ML-based method. Typically, the varying operational conditions of the power system are represented by altering the amplitude of the probing signal and system inertia. An LSTM-based method described in [127] for an islanded hybrid power system with distributed generators, WTG, fuel cells, and BESS presents an interesting approach to continuously monitoring the system inertia in microgrids. The inclusion of PID controllers for RESs to stabilize the system frequency is a practical consideration of this method. A periodic pulse is applied to the system, during the measurement of the system frequency. After adding noise and calculating the RoCoF, the frequency and RoCoF signals are fed to the LSTM model to process and classify temporal information. The training dataset includes frequency and RoCoF signals, with the system inertia collected by varying the system inertia and the amplitude of probing signal in the islanded hybrid power system. The results show that this method yields good performance in terms of the accuracy of time-varying inertia monitoring. Anyhow, the effects of tie-line dynamics have not been considered in this method.

The spatial feature of system inertia is identified by the CNN-based monitoring installed in the BESSs as perturbing and monitoring devices [128,129]. The aggregated single-machine model of the power system proposed in [130] is implemented to collect the dataset, including noisy frequency and RoCoF for training and validating the monitoring method [128]. In [129], the federated CNN-based method is used to monitor the regional inertia in a multi-region power system. In each area, one BESS perturbs the system that is non-synchronized with the other areas, measures the system frequency, and constructs the features to train the CNN-based method, including noisy frequency and corresponding RoCoF signals. After the training, the weights of local CNN models are sent to a central server. The central server updates the weights of each local CNN model based on the weighted average of all reached weights obtained from the clients for each time window. Indeed, the use of the decentralized method for system inertia monitoring can be highly advantageous for scenarios where centralized data collection from multiple areas may not be feasible or practical. This decentralized method does not require collecting a high volume of data from the entire power system, which can alleviate the burden on communication infrastructures and data storage. However, there are some drawbacks regarding the two mentioned methods: 1) the time-varying nature of system inertia is not considered, 2) the simple transfer function model of the power system cannot ensure the feasibility of these methods in real and complex power systems with acceptable accuracy, 3) the role of dynamic loads and RESs is ignored, and 4) the use of local frequency measurement may lead to high errors when non-monotonic frequency deviation occurs.

To tackle the above-mentioned issues and emulate realistic conditions, system inertia is monitored for a modified IEEE 39-bus test system, considering dynamic loads and WTG plants as shown in [131]. A ramp-like probing signal is injected by the converters on both sides of the HVDC transmission line for steady-state and disturbance conditions. The noisy frequency signal and perturbation amplitudes of are measured to train the feedforward ANN model. Several SGs have been replaced by WTG plants, which are not used for frequency control. Static loads based on a ZIP[1] model associated with frequency-dependent parameters are considered for training the ANN model, while the motor loads have been added for testing the model. This method relies on the existing infrastructure comprising HVDC transmission lines, and does not need widespread use of PMUs and extra equipment. However, it is capable of only monitoring the system inertia on two sides of the HVDC transmission line. Moreover, the use of dynamic loads in the only test stage is a questionable comment in terms of monitoring accuracy. Finally, the contribution of the virtual inertia of RESs has not been considered in this method.

The use of ambient measurements is proposed in [132,133]. In [132], the frequency and voltage signals of all buses are measured. Then, the dataset, which encompasses the frequency, corresponding RoCoF, and voltage signals associated with noise is used as the features. The best features, including the frequency and corresponding RoCoF signals within the first second after perturbation, are selected using a wrapper feature selection method. The LRCN-based method is trained and validated using a dataset constructed by varying system inertia and the amplitude of the probing signal in an IEEE 24-bus test system. A method called zero generation injection bus is proposed in [133] to optimize the placement and number of PMUs, and to maximize system's observability as well as to optimize the volume of input features. Besides, the GCN model apart from the LRCN is used for the comparison. Both ML-based methods have been efficient in identifying the important temporal and graphical information embedded in the collected power system dataset. Due to their inherent limitations in capturing long-term and spatial dependencies within graphs-stemming from the diffusion of information across multiple layers-GCNs may fall short. To address this issue, GATs are utilized in [134] to enhance the accuracy of system inertia monitoring. GATs achieve this by effectively capturing complex relationships and dependencies within power systems, thanks to their ability to assign varying levels of importance to different nodes. The frequency, and corresponding RoCoF signals associated with noise are as the features and the GATs-based method has been trained and tested by using the dataset presented in [132,133]. Table 4 shows the summary and relative comparison of perturbation-based methods.

5. Research and industrial projects related to system inertia monitoring comprising ML-based methods

Table 5 provides an overview of recent and ongoing research projects focused on monitoring system inertia using ML-based methods. In the project reported in [135], an ANN-based method is applied to monitor system inertia during normal system operation. The training dataset includes the cumulative active power of SGs, CIGs, directly connected induction motors, and the power line loading. Furthermore, they conducted HIL testing to validate the practical applicability of their proposed method [118]. Another project, reported in [136], aims to achieve precise day-ahead and intra-day forecasts of kinetic energy as system inertia. In this study, various input features are selected, including demand, generation capacity, interconnected power flow, electricity prices, inertial response, and day-ahead forecasts of loads, transmission systems, and RESs. These features are used to construct a probabilistic ML-based method that accurately and cost-effectively quantifies the forecast uncertainties. The method's performance is evaluated using historical data from the power systems in the United Kingdom and the Nordic region [137,138]. The forecasted inertia could potentially support day-ahead frequency response procurement and real-time system operations. The project described in [139] focuses on perturbation-based inertia monitoring using the LSTM-based method. Specifically, the researchers considered the impact of the frequency contributions of RESs on the frequency of an isolated grid. By measuring the frequency and RoCoF after introducing a perturbation signal, they developed an LSTM-based inertia monitor [127]. Additionally, researchers in [140] explore the effective monitoring of regional inertia and they use ML-based methods to monitor the inertia of regional power systems.

In practical terms, the monitoring of system inertia and kinetic energy in real power systems have gained significant attention. Many power systems have implemented tools for measuring system inertia by monitoring the operational state of SGs. Notably, the Electric Reliability Council of Texas (ERCOT) [141], the Nordic region [142], Vietnam [143], and India [144] have adopted such tools. Then, companies like Reactive Technologies have developed an innovative method to determine the kinetic energy, as illustrated in Fig. 13 [145]. This technology utilizes supercapacitors as modulators to intentionally perturb the power system, inducing fluctuations in the system frequency. The eXtensible Measurement Units (XMUs) distributed throughout the grid detect these frequency variations corresponding to the power pulses and relay the data to the processing platform for monitoring the system inertia.

These ground-breaking devices are initially deployed by the National Grid Electricity System Operator (ESO) in the United Kingdom [146]. The National Grid ESO claimed that United Kingdom customers save $19.6 million annually on managing system inertia, which is achieved by eliminating the need of purchasing excessive energy reserve margins [147]. Moreover, with precise and real-time measurements of grid inertia, power system operators may enhance the efficiency of mitigating the risk of grid instability and blackouts. These two advantages are illustrated in Fig. 13 for the case of inertia measurement in the United Kingdom [148]. Fig. 14 shows how the potential cost-saving

[1] Impedance(Z), Current (I), Power (P).

Table 4
Comparison of perturbation-based inertia monitoring.

Ref.	Type of monitoring	ML model	System type and considerations	Input features	Pros/Cons
[125]	System inertia	ANN	Single-machine model associated with a WTG and a PV	Size of perturbation; initial RoCoF;	+ Inertia monitoring during normal and disturbance conditions; − Simple power system model; − Ignoring noise in measurements;
[127]	Microgrid inertia	LSTM	Islanded microgrid including SG, WTG, BESS, and fuel cell; RESs contribute to frequency stabilization;	Noisy frequency signal; Noisy RoCoF signal;	+ Monitoring of time-varying inertia; − Not considering the tie-line dynamics;
[128]	System inertia	CNN	Aggregated single-machine model; BESS perturbs the system;	Noisy frequency signal; Noisy RoCoF signal;	− Simple power system model and measurements; − Not considering the dynamic loads and RESs
[129]	Regional inertia	FL	Two-area single-machine model; BESS in each area perturbs the system	Noisy frequency signal; Noisy RoCoF signal;	+ Distributed monitoring of inertia; − Simple power system model and measurements; − Not considering the dynamic loads and RESs
[131]	System inertia	ANN	IEEE 39-bus system model; HVDC Converters perturb the system; SGs are replaced by WTG plants;	Size of perturbation; Noisy frequency signal; Voltage of selected busses;	+ Inertia monitoring during normal and disturbance conditions; + Perturbation and monitoring by the available infrastructure; − Not considering the virtual inertia of RESs; − Only measuring the frequency at one point for monitoring;
[132]	System inertia	LRCN	IEEE 24-bus system model;	Noisy frequency, RoCoF, and voltage signals of all busses;	− Not considering the virtual inertia of RESs;
[133]	System inertia	GCN; LRCN;	IEEE 24-bus system model; Optimal placement of PMUs;	Noisy frequency and RoCoF signals of selected busses; Voltage signals of all buses;	− Not considering the virtual inertia of RESs;
[134]	System inertia	GAT	IEEE 24-bus system model;	Noisy frequency, and RoCoF signals of all busses;	− Not considering the virtual inertia of RESs;

(green area) and risk (red area) zones are determined by precisely measuring of the system inertia. Subsequently, this technology has been adopted by numerous power systems worldwide, including Australia [149], Taiwan [150], Japan, New Zealand, and Italy [147]. In Australia, Australian renewable energy agency claimed that continuous measurement of inertia has proven extremely valuable, enhancing grid operations and enabling the integration of greater amounts of solar and wind energy into electricity grids [151]. In addition to these tools and devices used for system inertia monitoring, ERCOT has developed a forecasting tool to determine the kinetic energy over a rolling 168-hour period. This

Table 5
ML-based system inertia monitoring research projects.

Project Name	Founded by (Name/ Country)	Key Features	Test System
Lessons learned from monitoring & forecasting key performance indicators on Impact of power electronics penetration [135]	European Union's horizon 2020 research and innovation programme- European Union	System inertia monitoring; Normal operation-based; ANN-based method; Based on power flow analysis;	IEEE 9-bus system
Short-term system inertia forecast [136]	National Grid ESO through network innovation allowance- United Kingdom	Day ahead system inertia forecast; Quantify forecast uncertainties;	UK and Nordic power systems
Characterization and detection of power system ambient, transient and forced oscillations based on PMU data analytics in Indian context [139]	Central power research institute- India	Perturbation-based; LSTM-based method; Frequency contribution of RESs;	Islanded microgrid model
Effective regional inertia monitoring and automatic control with a whole system approach [140]	Smarter power energy networks transmission- United Kingdom	Regional inertia monitoring;	

forecast relies on the unit commitment plans submitted by the generators on an hourly basis [152]. Reliability unit commitment is necessary during periods when inertia levels are insufficient. ERCOT also incorporates historical system inertia data to assess the requirements for responsive reserve service, adjusting the amounts needed based on varying inertia conditions [153].

Despite the existence of established monitoring and forecasting tools and devices, for many power systems with high level of RES integration, companies specializing in power system control and operation have begun to develop inertia monitoring tools and devices based on ML-based techniques. One noteworthy example is General Electric (GE), which has introduced a system inertia monitor utilizing ML-based methods [143]. This innovative tool is designed to measure and predict effective inertia on both regional- and global-scale. It claims to provide a comprehensive measure of effective inertia, encompassing the inertia of the rotating synchronous generations as well as the inertia-like effects of non-synchronous generations, such as WTG and PV systems, as well as the passive responses from domestic and industrial demand. By applying ML-based methods, inertia can be forecast, utilizing the data from both generation and demand. Regional inertia is also monitored using the area RoCoF and net boundary power, derived from the measurements of grid frequency and power flows. Recently, this device has been implemented in the National Grid ESO of the United Kingdom [154]. Siemens Energy is another company introducing a system for monitoring system inertia through power electronics converters. These converters can be periodically activated to provide crucial information to system operators. The method developed by Siemens Energy involves injecting a known perturbation by using converters and analyzing the network's frequency response to this perturbation to monitor the system inertia. This monitoring technology employs an ML-based method to accurately monitor system inertia by taking into account real power system features such as generator controller actions, load–frequency dependencies, and power system oscillation modes [155].

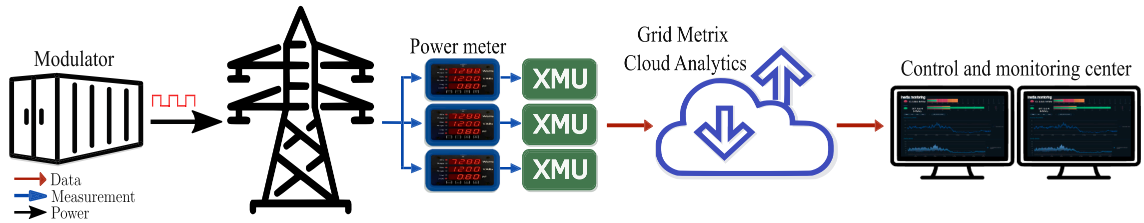

Fig. 13. Architecture of system inertia monitor developed by [145].

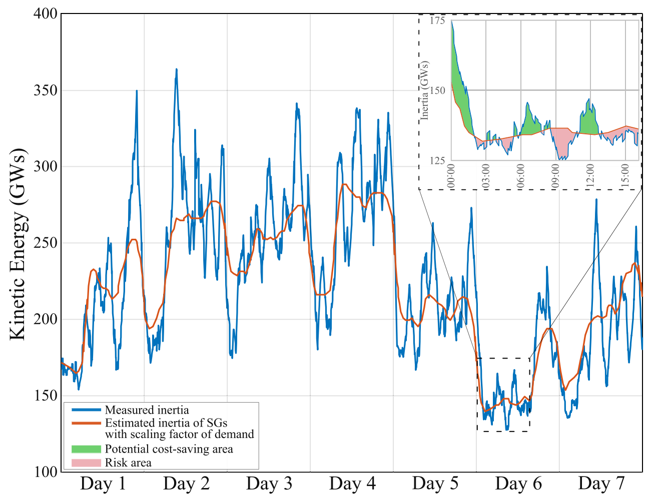

Fig. 14. Result of real-time monitoring of system inertia in the United Kingdom [148].

6. Applications of system inertia monitoring and ML-based methods for power system studies

Monitoring spatial–temporal system inertia in modern power systems offers opportunities for its application in diverse areas such as analysis, control, protection, and optimization. Moreover, ML-based methods can leverage this potential to tackle the challenges posed by complex power systems that are heavily integrated with RESs, thanks to their powerful capability to handle large amounts of multi-dimensional data.

The estimation of frequency response characteristics stands out as one of the most intriguing applications of system inertia monitoring in conjunction with ML-based methods. Predicting the frequency nadir has become a more challenging task due to the increasing penetration of RESs, which have significantly altered the generation portfolio of the power systems. In [156,157], the frequency nadir is estimated by employing ANN as the model. In [156], the input features of the ANN include the disturbance size and available kinetic energy of the system as system inertia. Meanwhile, [157] uses the load bus voltages, frequency variations after an event, system inertia, and event size to train the ANN-based method. To determine the best model and dataset in terms of estimating accuracy of frequency nadir, a comparative analysis is conducted in [158], where five types of models and two datasets are evaluated. The applied models include ANN, XGBoost, linear regression, gradient boosting, and support vector regression. The datasets used for training encompass the unit generation dataset, and system inertia and headroom dataset. Ultimately, XGBoost- and gradient boosting-based methods trained by the system inertia and headroom datasets achieve the highest estimating accuracy. In another research effort [159], the focus shifts to estimate the frequency response parameters following a disturbance, including frequency nadir, maximum RoCoF, and steady-state frequency. XGBoost-based algorithm is employed for prediction and is trained using variables such as system inertia, total system load demand, system spinning reserve, aggregated available kinetic energy from online SGs, disturbance size, and event location.

Power system operatorsrely on predicting frequency response characteristics to assess the frequency security of the system, as these characteristics are indicative of the impact of a sudden loss of a generating resource or connection of a large load. The monitoring of frequency response characteristics holds significance in applications such as frequency-constrained unit commitment and economic dispatch. In the context of security-constrained unit commitment and economic dispatch, the prediction of frequency nadir and RoCoF is addressed using ANN as a supervised learning-based approach reported in [160]. This ANN-based method takes into account the key features, including the power outputs of thermal generation units, and WTG and PV plants, spinning reserves, and system inertia. This method not only determines the additional inertia required for the islanded power systems with high RESs penetration but also aims to minimize the associated costs related to the inertia support from the energy sources. In [161], the estimation of frequency nadir and a parameter called stepwise frequency constraint, which enhances frequency recovery performance, are explored for the frequency-constrained unit commitment. Here, system inertia is among the input features used to train and validate a conservative sparse neural network-based algorithm. The output of the ML-based method is then transformed into constraints that are incorporated in conventional unit commitment model.

The objective of the ML-based method proposed in [162] is to enhance the accuracy of disturbance size estimation compared to the traditional estimation methods. In this approach, the disturbance size estimations generated by three traditional methods, based on equation (10), utilizing parameters such as system inertia and RoCoF (including locally measured RoCoF, the median of all measured frequencies, and the center of inertia), serve as the inputs to an MLP-based method. This method is trained by data collected from thirty-two confirmed disturbances in the WECC system to minimize the estimation errors associated with the traditional methods.

Determining the fast frequency reserve is yet another valuable application of system inertia monitoring in combination with ML-based methods. In [163], the frequency nadir estimation plays a pivotal role in a planning process that quantifies the capacity of fast-responsive reserve resources in the ancillary service market. This proposed plan has proven successful in maintaining the frequency nadir above the security criterion and preventing under-frequency load shedding across the various penetration levels of RESs. An XGBoost-based method is trained and deployed to predict the frequency nadir, with system inertia being one of the selected features. In [112,164], the target is to procuring the fast frequency reserve for PV plants participating in the system frequency stability. Here, an ANN-based method is trained using system inertia, system governor capacity, and frequency nadir set point. ANN-based method is employed to adjust the headroom set points of the frequency controllers for the PV plants. The results indicate headroom savings of at least 40 % compared to the traditional strategies, showcasing the effectiveness of this approach in optimizing frequency reserve management. A fast security monitoring method has been proposed by integrating ML-based methods in [165]. This method employs the Gaussian processing regression model to monitor the security of the power system. Additionally, the incremental Naïve Bayes algorithm is used to estimate the amount of load to be shed and determine the specific bus for the load shedding operations. The ML-based methods are trained using various parameters, including system inertia, load levels, fault locations, and power dispatched from RESs. Finally, in [166] a methodology is proposed to determine an optimal load shedding amount to prevent enabling the under/over-frequency protective relays based on ML-based methods. The target of this approach is to determine the amount of load to be increased and decreased in islanded areas following a separation of power system in two islands due to tie-line tripping. An ANN-based method is trained and evaluated by the features encompassing total generation and load, system inertia, power output and inertia of each generator, and power of each load.

While ML-based applications utilizing system inertia have been introduced in the literature, there remain numerous unexplored avenues for leveraging ML-based methods in conjunction with system inertia monitoring. Moreover, the existing applications have the potential to improve and further develop existing limitations. Table 6 summarizes the applications of system inertia monitoring and ML-based methods.

7. Conclusion and future directions

This paper provides a comprehensive overview of existing inertia monitoring methods that utilize ML-based techniques, offering guidance for researchers involved in the application of intelligent methods for inertia monitoring as well as discussing academic and industrial projects related to this subject. We have examined the ML-based methods employed in inertia monitoring to shed light on how knowledge is extracted based on the type of training features used. The monitoring methods have been categorized into three main groups: contingency-, normal operation-, and perturbation-based methods, and we have discussed the advantages and disadvantages of each group. Although there is a limited amount of literature regarding the applications of monitored inertia in fields utilizing ML-based methods, we have explored these applications within the scope of this review. We anticipate that this review will serve as a valuable reference and source of inspiration for future research in this area. Despite the significant progress made, there remain several unresolved issues, some of which are highlighted below:

- **Monitoring of the virtual inertia of RESs:** The interplay between the virtual inertia provided by RESs and the spatial–temporal distribution of system inertia is of paramount importance. On one side, RESs contribute to complex virtual inertia that depends on factors such as synchronous inertia (inertia from online SGs), frequency dynamics, and their operational constraints. On the other hand, synchronous inertia varies based on the number of online synchronous generators, influenced by the amount of virtual inertia supported by RESs and weather conditions. This complex interdependence between synchronous inertia, virtual inertia, and frequency dynamics must be taken into account when monitoring system inertia. Given that ML-based methods excel at extracting knowledge from complex and voluminous datasets with high dependencies, they can be effectively employed to monitor both virtual inertia and system inertia. It is worth noting that existing inertia monitoring methods using ML-based algorithms often overlook this intricate dependency and do not consider the monitoring of virtual inertia. However, there is a limited amount of literature on monitoring the equivalent virtual inertia of RESs using ML-based methods, particularly when considering the frequency and operational limitations of these energy sources [167]. Therefore, a promising research direction involves developing ML-based approaches to monitor system inertia, particularly in conjunction with the virtual inertia supported by RESs, including WTG and PV plants, while accounting for their operational constraints in both normal and contingency operations. This approach would provide a more comprehensive and accurate assessment of system inertia in modern power systems.
- **System inertia monitoring in the case of inaccurate or unavailable inertia information:** In all aforementioned inertia monitoring methods, the inertia data is available and is used in the training data. The ML-based problem is supervised learning. In many real-world scenarios, obtaining precise inertia information can be challenging, and this limitation must be considered when developing ML-based techniques for inertia monitoring. Besides, the development of methods for enriching the available datasets can make ML-based methods to be more accurate and robust.
- **Cyber-security considerations:** In the existing studies, ML-based algorithms have shown remarkable capabilities in terms of accuracy and performance for a wide range of applications. However, ML-based methods are indeed heavily influenced by the quality and trustworthiness of the data they operate on. As power systems become increasingly connected and reliant on data from various sources, they indeed become more susceptible to threats like false data injection and denial of service attacks, which can significantly impact the stability and reliability of the grid. In this regard, it is critically important to assess the vulnerability and potential impact of ML-based monitoring methods, particularly in the context of the growing threat of cyberattacks. The development of a methodological framework, as outlined in [168], to assess the vulnerability of ML-based inertia monitoring methods against data integrity attacks is a commendable step toward enhancing the security and reliability of power systems. There still exists a need for further impactful research and development to assess the vulnerability of ML-based methods in terms of cybersecurity, detect the attacks, and build robust ML-based system inertia monitoring methods for mitigating cyberattacks by conducting strategies such as adversarial training, anomaly detection methods, and so on.
- **HIL testing:** HIL methodology plays a pivotal role in advancing and testing complex systems across various industrial applications. It achieves this by seamlessly integrating a real-time simulation platform with the hardware and control devices under examination. The inclusion of power and flexibility offered by the HIL framework positions this testing method as a highly promising tool for versatile

Table 6
Applications of system inertia monitoring and ML-based methods.

Application	Target	ML model	Ref.
Frequency response characteristics estimation	Estimation of frequency nadir	ANN	[156,157]
		XGBoost and gradient boosting	[158]
	Estimation of frequency nadir, max. RoCoF, steady-state frequency	XGBoost	[159]
Security-constrained unit commitment	Optimization of cost of inertia support of RESs by estimating frequency nadir and RoCoF	ANN	[160]
	Estimation of frequency nadir and stepwise frequency constraint	Conservative sparse neural network	[161]
Disturbance size estimation	Improve the accuracy of traditional estimation methods	MLP	[162]
Determining fast frequency reserve	Determination of fast-responsive reserve to avoid load shedding	XGBoost	[163]
	Adjust headroom set point of frequency controller of PV plants	ANN	[112,164]
Security monitoring and load shedding plan	Security prediction and determination of the location and amount of load to be shed	Gaussian processing regression and incremental Naïve Bayes	[165]
	Determination of the optimal load shedding amount	ANN	[166]

testing and validation of applicable methods in low inertia power systems, both at the equipment and system-wide levels [169,170]. In the current landscape of literature concerning system inertia monitoring by ML-based methods, most developed methods are constructed and validated within simulation studies, despite using HIL testing in inertia monitoring based on other methods [171]. However, compared to conventional simulation tools, HIL simulation offers a more efficient, rapid, and realistic real-time simulation with heightened accuracy. Numerous technologies including OPAL-RT [172–176], Real-Time Digital Simulator (RTDS) [177,178], National Instruments (NI) [179,180], Speedgoat [181], and Programmable Logic Controller (PLC) [182], have been developing their capabilities to accommodate ML-based approaches. This makes it an attractive avenue for the development and exploration of ML-based system inertia monitoring methods. It is a possible future research direction with the potential to address various limitations and challenges in this field, including real-time interaction between the ML-based algorithms and physical hardware, and hardware compatibility and adaptability. Further future direction can be seen in scalability and complexity considerations in large-scale power systems or complex ML-based methods, cost and availability of the necessary system hardware, and safety and risk factors associated with HIL testing.

- **Applications of system inertia monitoring and ML-based methods:** The significant potential of applications that leverage both system inertia monitoring and ML-based methods can enhance the analysis and decision-making processes of modern power systems. These applications span various aspects of power system operation and management and can greatly benefit from the synergy between system inertia information and ML capabilities. The applications can include frequency security and stability assessments, frequency control of RESs, load shedding plans, design of protection plans, reserve planning, inertia allocation and market, inertia-based optimal power flow, and unit commitment. While some of these applications have been reviewed and explored in the current paper and related research, there is still substantial room for further investigation and development in the field of power system studies.
- **Application of near real-time ML-based methods:** As known, the quality of training procedures is determining the efficacy of ML-based techniques for different applications in electrical power and energy systems. In this context, ML-based approaches for inertia monitoring can underperform when the system state is not close to the system state used for training purposes. One of the typical challenges can be frequent changes in system topology, which can be caused by intentional, or/and unintentional topological changes. In conclusion, the offline training sets may not be sufficient enough to represent adequately the actual system behavior. Therefore, by using (near) real-time training data sets and updating the ML-based algorithm, the quality of the system inertia could be improved. The described approach is referred to a class of the incremental learning methods. In [183] such an approach was successfully applied. We trust that the incremental learning-based approach has a good potential for improving the efficacy of inertia monitoring algorithm and it should be further explored in the future.

CRediT authorship contribution statement

Mahdi Heidari: Writing – original draft, Investigation, Conceptualization. **Lei Ding:** Supervision, Investigation, Conceptualization. **Mostafa Kheshti:** Writing – review & editing, Conceptualization. **Weiyu Bao:** Writing – review & editing, Project administration, Conceptualization. **Xiaowei Zhao:** Resources. **Marjan Popov:** Writing – review & editing, Conceptualization. **Vladimir Terzija:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

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

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