Critical Assessment of Machine Learning-Based Approaches for Predicting System Inertia in Power Systems

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***Abstract*—The increasing integration of renewable energy sources in power systems has led to declining system inertia, making power grid stability a significant challenge. Machine learning (ML) techniques have emerged as a promising approach to predicting system inertia and enhancing grid stability. This paper critically assesses various ML-based methods for predicting system inertia in power systems. We will discuss the current state of research, the challenges and limitations of existing ML approaches, and potential future directions for improving prediction accuracy and real-world implementation. This paper aims to provide researchers and practitioners with a comprehensive understanding of ML-based system inertia prediction techniques and their applicability in modern power systems.**

Keywords: system inertia, machine learning, power grid stability, renewable energy integration, inertia prediction

I. Introduction

Maintaining stability in modern power systems guarantees consumers a consistent and dependable electricity supply. System inertia, which represents the inherent capability of a power system to counteract frequency fluctuations, is vital for sustaining power grid stability. The increasing integration of renewable energy sources, such as wind and solar, has decreased system inertia due to the diminished presence of traditional synchronous generators. This reduction presents considerable challenges for power grid stability, making the precise prediction of system inertia critical for efficient grid management and control [1].

Machine learning techniques have gained significant attention recently as a potential solution for predicting system inertia in power systems. These approaches leverage historical and real-time data to learn patterns and make predictions, offering a data-driven alternative to traditional model-based techniques. This paper critically assesses various ML-based approaches for predicting system inertia, highlighting their advantages and limitations and identifying potential areas for future research.

II. Current Scenario and Challenges

A. Introduction

The power system landscape has significantly changed in recent years, driven by the global push towards cleaner and more sustainable energy sources. The increasing integration of renewable energy resources, such as wind and solar, transforms how power grids are operated and managed. While renewable energy brings numerous benefits, such as reduced greenhouse gas emissions and lower dependency on fossil fuels, it also introduces new challenges for power grid stability. One of the most pressing issues is the decline in system inertia, which is crucial for maintaining frequency stability and grid reliability [2].

B. Decline in System Inertia

System inertia refers to the inherent ability of a power system to resist changes in frequency. Conventional power systems such as coal, gas, nuclear power plants and synchronous generators provide most of the system inertia [3]. These generators have huge rotating masses, which store kinetic energy and help maintain a stable frequency in the grid by resisting sudden changes in the power supply or demand.

On the other hand, renewable energy sources are generally connected to the grid through power electronic converters, which decouple the electrical energy and the mechanical inertia of the generator. As a result, these resources contribute little to inertia to the power system. The increasing penetration of renewable energy resources displaces conventional synchronous generators, leading to a decline in system inertia [4].

C. Challenges Posed by Renewable Energy Integration

1. Frequency Stability

The decline in system inertia makes power systems more susceptible to frequency deviations following disturbances, such as load changes or generator outages. Lower system inertia results in more significant and faster frequency deviations, leading to unsafe system operation and, in extreme cases, cascading failures and blackouts [5].

2. Variability and Uncertainty

Renewable energy sources, particularly wind and solar, are characterized by high variability and uncertainty in their power output. This variability introduces additional challenges for maintaining power balance and grid stability, as operators must manage the fluctuations in power supply and demand [6].

3. Limited Predictability

The output of renewable energy sources depends on weather conditions and other environmental factors, which are difficult to predict accurately. This limited predictability complicates forecasting power generation and managing power system resources to maintain grid stability [7].

4. Need for Advanced Control Strategies

The integration of renewable energy sources necessitates the development of advanced control strategies to mitigate the challenges associated with lower system inertia. These strategies may include deploying energy storage systems, demand response programs, and advanced grid management techniques [2].

D. The Need for Accurate System Inertia Prediction

Accurate prediction of system inertia is essential for maintaining power grid stability in increasing renewable energy integration. Operators and control systems need precise information on system inertia to make informed decisions about grid management, such as dispatching generation resources, implementing load shedding, or activating frequency response services [8].

Traditionally, system inertia has been estimated using static models based on the characteristics of synchronous generators. However, these models may no longer be sufficient for modern power systems with high renewable energy penetration, as they do not adequately capture the dynamic nature of system inertia in such systems. Consequently, there is a growing interest in developing data-driven methods, such as machine learning-based approaches, for predicting system inertia [9].

Machine learning techniques can improve the accuracy and timeliness of system inertia prediction by leveraging historical and real-time data to learn patterns and make predictions. However, the application of machine learning for system inertia prediction faces several challenges and limitations, which need to be addressed to ensure the effectiveness of these approaches in real-world power systems.

In conclusion, the current power system scenario is characterized by increasing renewable energy integration, which leads to a decline in system inertia and poses new challenges for power grid stability. Accurate prediction of system inertia is crucial for managing these challenges and ensuring the reliable operation of power systems. [3]. However, further research is needed to address these approaches' challenges and limitations and develop more accurate and robust methods for system inertia prediction in modern power systems with high renewable energy penetration.

E. The Role of Advanced Grid Management Techniques

1. Energy Storage Systems

Deploying energy storage systems, such as batteries and pumped hydro storage, can help mitigate the challenges associated with renewable energy integration by providing additional system flexibility and acting as a source of synthetic inertia. Energy storage systems can absorb or release energy rapidly, helping to maintain the power balance and stabilize the grid frequency [10].

2. Demand Response Programs

Demand Response Programs which involve adjusting the electricity consumption of participating users in response to grid conditions, can provide an additional means of managing power system stability. By adjusting demand in real-time, these programs can help to balance power supply and demand and alleviate the challenges posed by the variability and uncertainty of renewable energy sources [11].

3. Advanced Grid Management Techniques

Developing advanced grid management techniques, such as wide-area monitoring and control systems, can help operators better monitor and manage system inertia and overall grid stability. These techniques can provide real-time information on system conditions, enabling operators to make more informed decisions about the dispatch of generation resources and the activation of frequency response services [12].

4. Grid-Forming Inverters

Development and deployment of grid-forming inverters, which can provide synthetic inertia and emulate the behavior of synchronous generators, offer another potential solution for addressing the challenges of renewable energy integration. By providing synthetic inertia, grid-forming inverters can help to maintain power grid stability in systems with high renewable energy penetration [13].

E. The Importance of Cross-Disciplinary Collaboration

Addressing the challenges associated with system inertia prediction in power systems with high renewable energy penetration requires a cross-disciplinary approach involving collaboration between power system engineers, data scientists, and machine learning experts. By combining domain knowledge with advanced data-driven techniques, researchers can develop more accurate and robust methods for predicting system inertia and managing power grid stability in the context of increasing renewable energy integration [14].

In conclusion, the increasing integration of renewable energy sources in power systems has led to a decline in system inertia, posing significant challenges to power grid stability. Accurate prediction of system inertia is essential for managing these challenges and ensuring the reliable operation of power systems. Machine learning-based approaches have the potential to enhance system inertia prediction, but further research is needed to address the challenges and limitations associated with these approaches. Developing advanced grid management techniques and cross-disciplinary collaboration can help address these challenges and ensure the reliable operation of power systems with high renewable energy penetration.

III. Existing Machine Learning Approaches for System Inertia Prediction

As power systems evolve and renewable energy penetration increases, accurate system inertia prediction becomes more critical. Several machine learning (ML) techniques have been applied to predict system inertia, each with strengths and limitations. This section reviews and critically assesses various ML-based techniques for predicting system inertia, such as linear regression, support vector machines, neural networks, and ensemble methods.

A. Implementation A - Power System Inertia Estimation Using A Residual Neural Network-Based Approach

A prime example of a practical application of neural networks in research is the "Power System Inertia Estimation Using a Residual Neural Network-Based Approach"[16]. This approach employs a residual neural network (ResNet) to predict system inertia and addresses the challenges posed by the growing integration of non-synchronous generation into power grids. System inertia declines as converter-interfaced generators replace traditional synchronous generating units, resulting in more complex frequency regulation and control challenges. Monitoring and quantifying system inertia accurately are crucial for implementing corrective actions to maintain power system stability.

The suggested ResNet model utilizes the frequency of thecentre of inertia and the corresponding calculated frequency change rates during a predefined time interval as input data. The model accounts for sudden generation outages, load step changes, total load demand variations, and equivalent inertia reductions. Training the ResNet model on this data can estimate the equivalent inertia of a sample power system in real-time, enabling operators to take necessary actions to maintain system stability.

The practical implementation of this ResNet-based method allows power system operators to comprehend better and address the challenges stemming from the increased integration of non-synchronous generation. By offering more accurate inertia estimates, the ResNet model surpasses conventional machine learning techniques, such as Support Vector Machines and Random Forests, in predicting system inertia. This improved prediction capability enables more effective frequency regulation and control, ensuring the reliable and stable operation of power systems with high levels of non-synchronous generation.

The ResNet-based model for inertia estimation employs a deep neural network architecture specifically designed to handle residual connections. Regarding power system inertia estimation, the ResNet-based model uses the frequency of the centre of inertia and the corresponding calculated frequency change rates during a predefined time interval as input. These inputs are fed into a series of layers in the neural network, which use residual connections to enable the training of deep networks.

The ResNet-based model is trained on data gathered from time-domain simulations of power systems under various scenarios, such as sudden generation outages and load step changes, considering total load demand variations and equivalent inertia reductions. During training, the model learns to estimate the equivalent inertia based on these inputs and outputs, as shown in Fig. 2.[16, Fig 4].

Compared to other machine learning models, such as Support Vector Regression (SVR) and random forest, ResNet achieves higher accuracy in predicting system inertia under low-inertia scenarios caused by the integration of converter-interfaced generators. This is due to ResNet's ability to capture complex nonlinear relationships between input and output variables that may be challenging for other models to learn.

In summary, the ResNet-based model for inertia estimation represents a promising approach for maintaining stability in power systems with high renewable penetration. Nevertheless, neural networks have several disadvantages, including the requirement for extensive training data, the risk of overfitting, and the complexity of interpreting their internal structure and learning relationships. Additionally, training neural networks can be computationally intensive, particularly for deep architectures with numerous layers and neurons.

Fig. 1. displays the various layers and operations involved in the ResNet-based model for inertia estimation. Here is a summary of each layer [16, Fig 4]:

1. Input layer: This layer takes in the frequency of the centre of inertia and the corresponding calculated rate of frequency change for a predefined time interval.

2. Convolutional layers employ convolutional operations to extract meaningful feature maps from the input data.

3. Residual blocks: These blocks use residual connections to enable the training of intense networks. Each block contains two convolutional layers with batch normalization and ReLU activation functions.

4. Global average pooling layer: This layer computes the average value across all feature maps in each channel.

5. Fully connected layers: These layers use dense connections to map the extracted features to an output value, which is an estimate of the equivalent inertia value, which is an estimate of the equivalent inertia.

6. Output layer: This layer produces the final output value, representing the estimated equivalent inertia.

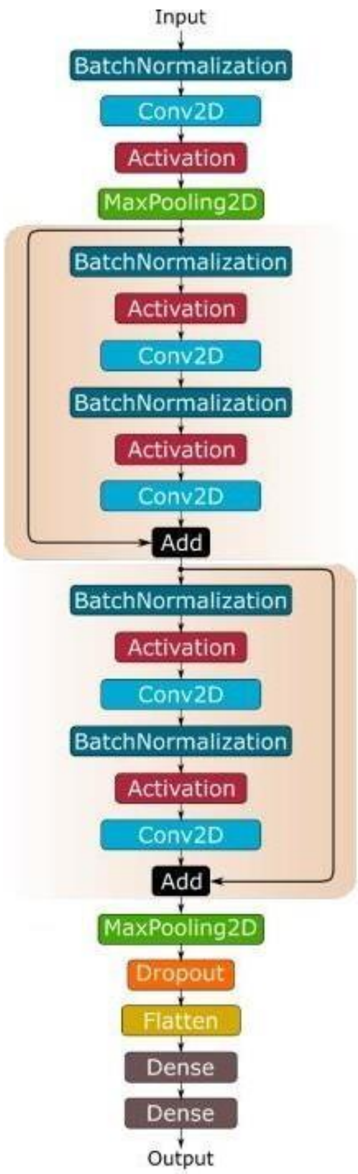

Fig. 1 . Graphical flow chart of the proposed model architecture

Overall, this architecture is designed to capture complex nonlinear relationships between input and output variables that may be difficult for other models to learn, making it a promising approach for maintaining stability in power systems with high renewable penetration.

B. *Implementation B - A Comparison of Machine Learning Methods for Frequency Nadir Estimation in Power Systems*

The study aims to evaluate five distinct machine learning techniques for estimating frequency nadir in power systems [17], emphasizing the necessity for precise frequency nadir predictions to enable power system operators to take preemptive measures against significant frequency fluctuations.

The five machine learning approaches assessed in this study include linear regression (LR), gradient boosting (GB), support vector regression (SVR), artificial neural networks (ANN), and XGBoost. The comparison utilizes two separate datasets: the unit generation dataset and the combined system inertia and headroom dataset, both produced by running PSS/E on the Western Electricity Coordinating Council 240-bus system.

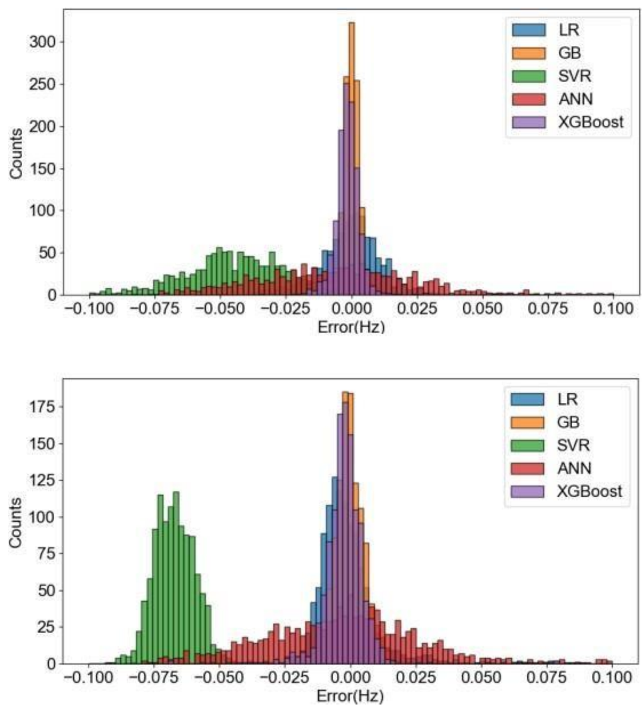

Fig. 2 . Error distribution of UGD (top) and TIH (bottom) testing of proposed model architectures

This research presents the error distribution for two different datasets: the unit generation dataset (UGD) and the system total inertia and headroom dataset (TIH). The error distribution is shown in Figure 2, with the UGD on top and the TIH on the bottom [17, Fig 5].

This research determines that all the machine learning techniques can achieve high performance in predicting frequency nadir, but a comprehensive comparison has yet to be carried out. As a result, this study addresses this gap by proposing two data preprocessing methods and comparing the five machine learning techniques.

After thorough simulations utilizing the Multi-timescale Integrated Dynamic and Scheduling (MIDAS) toolbox created by the National Renewable Energy Laboratory, the research determines that XGBoost outperforms other techniques in both accuracy and computational effectiveness. Nevertheless, it is essential to acknowledge that each method has advantages and disadvantages contingent upon the particular application context.

Gradient boosting achieves the best error distribution in both datasets, followed closely by XGBoost. In contrast, due to their high variance distribution, artificial neural networks (ANN) and support vector regression (SVR) are unsuitable for this work. Additionally, both methods perform worse in the TIH testing dataset.

It is worth noting that linear regression ranks third in both datasets, indicating its potential as a simple yet effective method for frequency nadir estimation in power systems. Overall, this error distribution analysis provides valuable insights into the performance of different machine learning methods for frequency nadir prediction.

In summary, this research study offers a robust understanding of employing machine learning methods for estimating frequency nadir in power systems. Comparing these five approaches can help power system operators choose an appropriate method based on their needs and constraints. Moreover, this research opens new opportunities to explore machine-learning techniques in renewable energy systems.

In conclusion, existing ML approaches for system inertia prediction, such as linear regression (LR), gradient boosting (GB), support vector regression (SVR), artificial neural network (ANN), and XGBoost and ResNet, offer varying levels of accuracy and complexity. Each technique has its strengths and limitations. Selecting the most appropriate method for a given power system scenario depends on factors such as data availability, computational resources, and the desired level of prediction accuracy. Further research is needed to develop more advanced ML techniques that can overcome the limitations of existing approaches and provide accurate and robust predictions of system inertia in power systems with high renewable energy penetration.

IV. Challenges And Limitations Of Machine Learning-Based Approaches

While machine learning (ML)-based approaches have demonstrated their potential in predicting system inertia in power systems, some several challenges and limitations need to be addressed to ensure their successful real-world implementation. This section discusses the main challenges and limitations, including data requirements, model interpretability, and real-world implementation challenges.

A. Data Requirements

One of the primary challenges in applying ML algorithms for predicting system inertia is obtaining sufficient high-quality data. Power systems are complex, and the relationships between system inertia and various factors, such as generation mix, load levels, and network topology, can be highly nonlinear and time-varying. To capture these relationships, ML models require large amounts of historical data, which may not always be readily available or accessible.

Moreover, data quality is critical for the success of ML models. Only accurate or complete data can lead to good model performance or misleading results. For instance, missing or incorrect measurements of generator speeds, loads, or network parameters can lead to inaccurate estimates of system inertia. Furthermore, outliers or noise in the data can adversely impact the model's ability to learn the underlying patterns and relationships.

Data preprocessing and feature engineering are essential steps in addressing these data-related challenges. Preprocessing techniques, such as data cleaning, imputation of missing values, and outlier detection, can help improve data quality. Feature engineering, on the other hand, involves selecting relevant input features and transforming them into a format that can be effectively used by ML algorithms [18]. This step is crucial for capturing the complex relationships between input features and system inertia and can significantly impact the performance of the ML models.

B. Model Interpretability

Another important challenge in applying ML algorithms for system inertia prediction is the need for more interpretability of some models, particularly complex ones such as deep neural networks [19]. Interpretability is important in the context of power systems. It can help operators and engineers understand the underlying relationships between input features and system inertia and provide insights into the factors affecting system stability.

While simpler models, such as linear regression and support vector machines with linear kernels, can provide interpretable predictions, their ability to capture complex, nonlinear relationships is limited. On the other hand, complex models, such as neural networks and ensemble methods, can provide more accurate predictions but are often considered "black boxes" due to their lack of interpretability.

Recent research has focused on developing techniques for improving the interpretability of complex ML models, such as layer-wise relevance propagation and local interpretable model-agnostic explanations (LIME). These techniques aim to provide insights into the inner workings of the models and help explain their predictions. However, further research is needed to develop more effective interpretability techniques and to assess their applicability to system inertia prediction.

C. Real-World Implementation Challenges

The successful implementation of ML-based system inertia prediction models in real-world power systems poses several challenges. One of these challenges is the integration of ML models with existing power system monitoring and control infrastructure. This requires the development of efficient algorithms and communication protocols to ensure that the ML models can effectively interact with existing systems and provide timely and accurate predictions.

Another challenge is the need to adapt ML models to the dynamic nature of power systems [20]. Power system conditions, such as generation mix and network topology, can change rapidly due to renewable energy integration, demand fluctuations, and equipment outages. ML models must adapt to these changes and provide accurate predictions under varying system conditions. This may involve updating the models with new data or fine-tuning their parameters in real time.

Furthermore, the robustness of ML models to uncertainties and disturbances in power systems is a significant concern.
Power systems are subject to uncertainties, such as forecasting errors in renewable generation and load and disturbances, such as equipment failures or weather events. ML models must be robust and resilient to these uncertainties and disturbances to provide accurate and reliable system inertia predictions. This may involve incorporating uncertainty quantification techniques, such as Bayesian or ensemble learning, into the ML models to account for power systems' inherent variability and unpredictability.

D. Scalability and Computational Complexity

ML models' scalability and computational complexity are significant challenges in system inertia prediction. Power systems are growing in size and complexity due to integrating distributed energy resources, such as solar photovoltaics, wind turbines, and energy storage systems [21]. As a result, the dimensionality of the input data and the complexity of the relationships between input features and system inertia are increasing.

ML models must scale effectively to handle large-scale power systems and provide timely predictions. This may require the development of more efficient algorithms and parallel processing techniques to reduce the computational complexity of the models. Additionally, hardware accelerators, such as graphics processing units (GPUs) or field-programmable gate arrays (FPGAs), can help improve the computational efficiency of ML models and enable their real-time implementation in power systems.

In conclusion, while ML-based approaches have shownpromise in predicting system inertia in power systems, several challenges and limitations must be addressed to ensure their successful real-world implementation. These include data requirements, model interpretability, real-worldimplementation challenges, and scalability and computational complexity. Further research is needed to develop more effective solutions to these challenges and to evaluate their impact on the performance and reliability of ML-based system inertia prediction models.

V. Future Scope And Potential Improvements

This section discusses potential areas for future research and improvements in ML-based system inertia prediction. These areas include incorporating domain knowledge, addressing data quality and availability issues, and developing more interpretable and robust models.

A. Incorporating Domain Knowledge

One of the key challenges in applying ML techniques to predict system inertia is the need for domain knowledge incorporated into the models. While data-driven approaches have shown promising results, incorporating domain knowledge can further enhance the performance and generalizability of ML models. By leveraging the knowledge of power system experts and engineers, future research can explore hybrid approaches that combine ML techniques with physics-based models to develop more accurate and reliable predictions.

For example, deep learning architectures that integrate domain-specific features and constraints, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), can be tailored better to capture the dynamics and dependencies in power systems. Researchers can also investigate using knowledge graphs and other structured representations of power system knowledge to guide the learning process and improve the interpretability of ML models.

B. Addressing Data Quality and Availability Issues

Data quality and availability play a crucial role in the performance of ML models for system inertia prediction. To ensure the effectiveness of ML-based approaches, future research should address challenges related to data collection, preprocessing, and integration.

Data collection can be improved by developing advanced sensors and measurement devices that provide more accurate and timely information about the state of power systems. Additionally, researchers can explore methods for data augmentation, such as generating synthetic data or using transfer learning techniques, to alleviate the issue of limited data availability [22].

Preprocessing techniques can also be improved to handle missing data, outliers, and other data quality issues better. Researchers can investigate methods for imputing missing values, detecting and correcting errors, and normalizing data to ensure consistent and reliable inputs for ML models.

Finally, data integration methods can be developed to combine data from multiple sources, such as phasor measurement units (PMUs), supervisory control and data acquisition (SCADA) systems, and other sensors, to provide a more comprehensive view of the power system and facilitate more accurate predictions [23].
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C. Developing More Interpretable and Robust Models

Interpretability and robustness are essential in implementing ML models for system inertia prediction. Future research should focus on developing accurate and easily understandable models by power system engineers and resilient to uncertainties and disturbances in power systems.
Researchers can investigate the use of explainable AI (XAI) techniques, such as feature importance analysis, decision tree-based methods, and visualization tools, to provide insights into the relationships between input features and predicted system inertia. This can help power system experts validate and refine the models, leading to better predictions and improved trust in the ML-based approach.

Developing robust ML models that can handle uncertainties and disturbances in power systems is also an important area of research. Techniques for uncertainty quantification, such as Bayesian approaches and Monte Carlo methods, can be explored to understand better and manage the impact of uncertainties on model predictions [24]. Researchers can also investigate methods for improving model robustness, such as adversarial training and regularization techniques, to ensure the stability and reliability of ML-based system inertia predictions in the presence of disturbances and noise.

In conclusion, the future scope and potential improvements in ML-based system inertia prediction are vast, and addressing these challenges can lead to significant advancements in power systems. By incorporating domain knowledge, addressing data quality and availability issues, and developing more interpretable and robust models, researchers can revolutionize power grid stability and facilitate the efficient integration of renewable energy resources.

CONCLUSION

This paper provided a comprehensive review and critical assessment of the existing machine learning (ML) approaches for predicting system inertia in power systems. ML-based techniques have shown great potential in enhancing the stability of power grids by accurately predicting system inertia. However, the integration of renewable energy sources and the evolving nature of power systems have introduced new challenges that need to be addressed to ensure the reliability and effectiveness of these techniques.

The graphical abstract has been created based on the research pipeline as shown in Fig. 3.

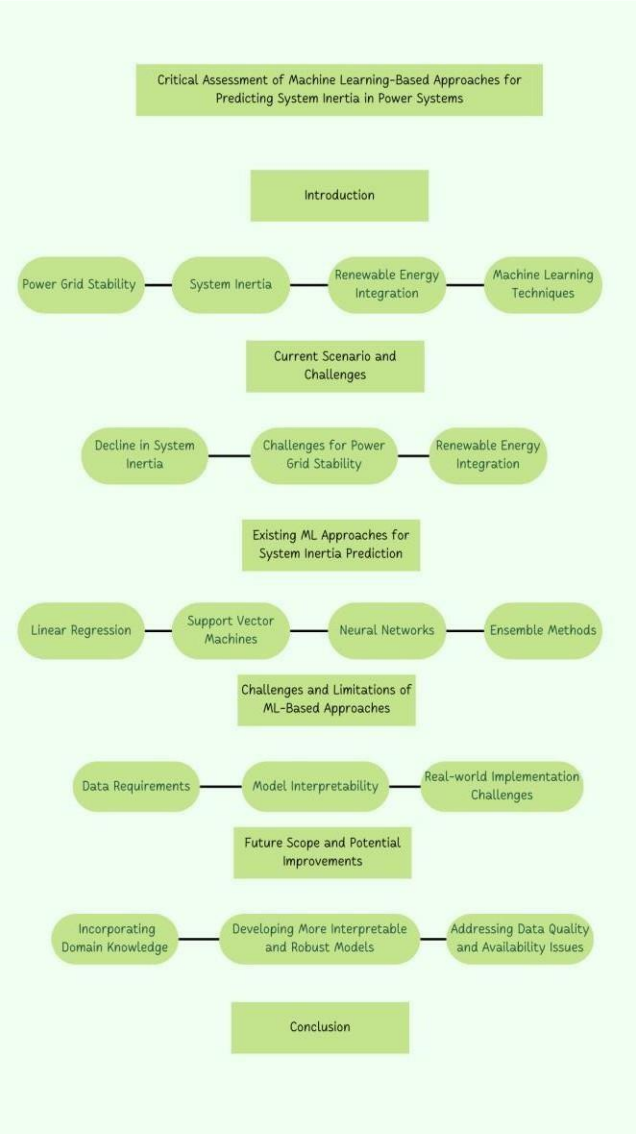

Fig. 3 . Graphical flow chart of the overall research

Several limitations and challenges in current ML-based approaches were identified, including the need for extensive and high-quality data sets, model interpretability issues, and real-world implementation challenges. Developing strategies for overcoming these challenges is essential, as they may hinder the progress of ML-based techniques in power systems. Furthermore, future research should incorporate domain knowledge, address data quality and availability issues, and develop more interpretable and robust models.

To conclude, despite the promise of ML-based approaches for predicting system inertia in power systems, several challenges and limitations must be addressed. By overcoming these obstacles and focusing on future research, the applicability and accuracy of these techniques can be significantly improved, ultimately contributing to the stability and reliability of modern power systems. The findings of this paper can serve as a valuable guide for researchers and practitioners alike, helping them make informed decisions when selecting and implementing ML-based system inertia prediction techniques.

ACKNOWLEDGMENT

I thank my colleagues, friends, and family for their unwavering support and motivation given during this research endeavour. and also, I am particularly indebted to the power systems and machine learning domain experts and professionals who have generously imparted their valuable knowledge and expertise, which allowed me to broaden my comprehension and enrich the substance of this paper. I am also grateful to the anonymous reviewers for providing constructive feedback that enhanced the paper's quality and coherence. Finally, I am thankful to the numerous researchers and scientists whose contributions form the backbone of this research paper, which inspired me to delve into new directions and add to the ever-growing body of knowledge in power systems and machine learning.

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