T.C.
BAHCESEHIR UNIVERSITY
GRADUATE SCHOOL
DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

FORECASTING OF WIND POWER GENERATION: A COMPARATIVE STUDY

MASTER’S THESIS

SHER YAR KHAN

ISTANBUL 2023

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ABSTRACT

FORECASTING OF WIND POWER GENERATION: A COMPARATIVE STUDY

SHER YAR KHAN

Master's Program in Electrical and Electronics Engineering

Supervisor: ASSIST. PROF. CAVİT FATİH KÜÇÜKTEZCAN

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Wind is an essential renewable energy source for producing power because of its reliability, global reach, and economic feasibility, and it has a growing share of global energy output. Particularly, Turkey is working on a renewable energy revolution to source 64% of its electricity from renewable energies by 2035. Wind power stands out among the renewables due to Turkey's favorable geographical positioning, which offers substantial wind energy potential. However, incorporating produced wind power into the current power transmission system is difficult due to wind's naturally unstable and intermittent behavior. Furthermore, power plant operators require reliable information on day-ahead power generation for market operations. As a result, forecasting of wind power approaches are becoming increasingly important in renewable energy research. This thesis investigates the production of wind power forecasting in depth, demonstrating the effectiveness of machine learning algorithms in predicting power outputs. SVM with the consideration of three different kernel function were all compared in the investigation. Two cases are considered to investigate the performance of implemented models in predicting wind power generation. Case I involves the time series analysis of dataset that was prepared to enable one-day forecasting on an hourly basis. Case II involves the forecasting of wind energy on weekly basis. It is observed that the SVM with Polynomial kernel outperforms the other models in both considered cases. It is important to note this analysis is performed using specific dataset so the performance of these models may vary with other considerations and under different parameter settings.

Keywords: Wind energy forecasting, ML, ANN, SVR, SVM.

ÖZET

RÜZGAR ENERJİSİ ÜRETİMİNİN TAHMİNİ: BİR KARŞILAŞTIRMALI ÇALIŞMA

SHER YAR KHAN
Elektrik ve Elektronik Mühendisliği Yüksek Lisans Programı
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Rüzgar, güvenilirliği, küresel erişimi ve ekonomik uygunluğu nedeniyle güç üretimi için vazgeçilmez bir yenilenebilir enerji kaynağıdır ve küresel enerji üretiminde giderek artan bir paya sahiptir. Özellikle, Türkiye 2035 yılına kadar elektriğinin %64'ünü yenilenebilir enerjilerden elde etme hedefi doğrultusunda bir enerji devrimi üzerinde çalışmaktadır. Türkiye'nin olumlu coğrafi konumu nedeniyle rüzgar enerjisi potansiyeli yüksektir, bu da rüzgar enerjisinin diğer yenilenebilir enerjilere göre öne çıkmasını sağlamaktadır. Ancak, üretilen rüzgar enerjisinin mevcut enerji iletim sistemine entegre edilmesi, rüzgarın doğal olarak kararsız ve aralıklı davranışı nedeniyle zordur. Ayrıca, enerji santrali operatörleri, piyasa operasyonları için önceden güç üretimi hakkında güvenilir bilgilere ihtiyaç duymaktadır. Bu nedenle, rüzgar enerjisi tahmin yaklaşımları, yenilenebilir enerji araştırmalarında giderek daha önemli hale gelmektedir. Bu tez, rüzgar enerjisi tahmininin üretimini derinlemesine inceleyerek, makine öğrenimi algoritmalarının güç çıkışlarını tahmin etmedeki etkinliğini göstermektedir. Üç farklı çekirdek fonksiyonunu içeren SVM modelleri karşılaştırılmıştır. Uygulanan modellerin rüzgar enerjisi üretimini tahmin etmedeki performansını araştırmak için iki vaka ele alınmıştır. Vaka I, saatlik bazda bir günlük tahmin yapabilmek için hazırlanan veri setinin zaman serisi analizini içermektedir. Vaka II, haftalık bazda rüzgar enerjisi tahminini içermektedir. Gözlemlendiği üzere, SVM modeli Polynomial çekirdek ile diğer modellere göre her iki durumda da daha başarılıdır. Bu analizin belirli bir veri

kümesi kullanılarak gerçekleştirildiğini belirtmek önemlidir, bu nedenle bu modellerin performansı diğer faktörler ve farklı parametre ayarları altında değişiklik gösterebilir.

Anahtar Kelimeler: Rüzgar enerjisi tahmini, Makine Öğrenimi (ML), Yapay Sinir Ağları (ANN), Destek Vektör Regresyonu (SVR), Destek Vektör Makineleri - Polinom (SVM-Poly), Destek Vektör Makineleri - Lineer (SVM-Linear), Destek Vektör Makineleri - Radial Basis Function (SVM-RBF) yöntemleriyle ilgili olarak.

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Lastly, but not the least, I extend my thanks and dedicate this study to my family, my parents, siblings, and friends for their unwavering support, motivation, encouragement, and inspiration throughout my life. They have consistently been a beacon of light for me.

Above all, I express gratitude to Allah Almighty, the Source of Knowledge and Wisdom, for His Boundless Love, which has made this endeavour possible.

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LIST OF ABBREVIATIONS

TWh	Terawatt-Hours
GW	Giga Watt
ML	Machine Learning
ANNs	Artificial Neural Networks
SVM	Support Vector Machine
NNs	Neural Networks
NWP	Numerical Weather Prediction
WS	Wind Speed
WP	Wind Power
ARMA	Autoregressive Moving Average
SWAR	State Vector Autoregressive
MLP	Multi-Layer Perceptron
PAR	Power Autoregressive
SVR	Support Vector Regression
CNN	Convolutional Neural Network
STCM	Spatiotemporal Correlation Modelling
SCADA	Supervisory Control & Data Acquisition
WNN	Wavelet Neural Network
BPNN	Back-Propagation Neural Network
RBFNN	Radial Basis Function Neural Network
ENN	Elman Neural Network
RNN	Recursive Neural Network
LSTM	Long-Short-Term Memory
DGF	Double Gaussian Function
ADAM	Adaptive Moment Estimation
MAE	Mean Absolute Error
MSE	Mean Squared Error

RMSE	Root Mean Squared Error
NRMSE	Normalized Root Mean Squared Error
MAPE	Mean Absolute Percentage Error
AWNN	Adaptive Weighted Neural Network
RF	Reinforcement Learning
IF	Isolation Forest
LSSVM	Least Square Support Vector Machine
ANFIS	Adaptive Network-based Fuzzy Inference System

Chapter 1

Introduction

Renewable energy supplies are gaining popularity as the global environment deteriorates and fossil fuels run out. The development and use of sustainable energy is critical for protecting the environment and has grown to be a global concern. Excessive use of traditional fossil fuels, such as hydrocarbon fuels, for energy production has resulted in significant worldwide air pollution as well as global warming. Renewable energy is the energy that comes from naturally regenerated sources such as the sun and wind. Renewable energy is not harmful to the environment at energy generation's plants, and has a far lower footprint on the environment than conventional energy from installation to decommissioning, as well as the ability to diversify power producing technology. In addition, growing population necessitates more sustainable energy development.

Wind energy is known as one of the most popular renewable energy sources. Wind energy is regarded as an approved renewable due to its ability to mitigate the effects of climate change and attain low-carbon transformation Wind energy is advantageous in comparison to other forms of energy since it is free, clean, unlimited, capable of producing more power, and has lower energy costs. Furthermore, generating electrical power from the wind is a straightforward process. In a nutshell, a wind turbine turns the kinetic energy of the wind into the mechanical, which can then be transformed into electrical power by a generator. However, the wind has an intrinsic tendency to change, and wind power can thus be regarded a fluctuating electrical power source. Geographical constraints, public opposition, animal conservation, and energy grid integration all pose problems for developers and planners when it comes to wind generating plant placement. Although wind speed is the key consideration in choosing a location for wind turbine positions, economic, social, environmental, and political requirements are beginning to be considered in order to successfully manage the land use limitations of energy sources while determining wind farm potential.

According to REN21's Renewables 2023 worldwide Status Report, the renewable share of worldwide power generation climbed by 8.1% to 29.9% in 2022 (Renewables, 2023). Figure *1* shows the global cumulative installed capacity of the wind power for year 2001 to 2022. It can be seen that the capacity of the wind power installed worldwide reached to approximately 900 gigawatts. China and the United States contributed for slightly more compared to other countries. Their contribution is about three-quarters of the global increase in power output in 2020 (Statista, 2023).

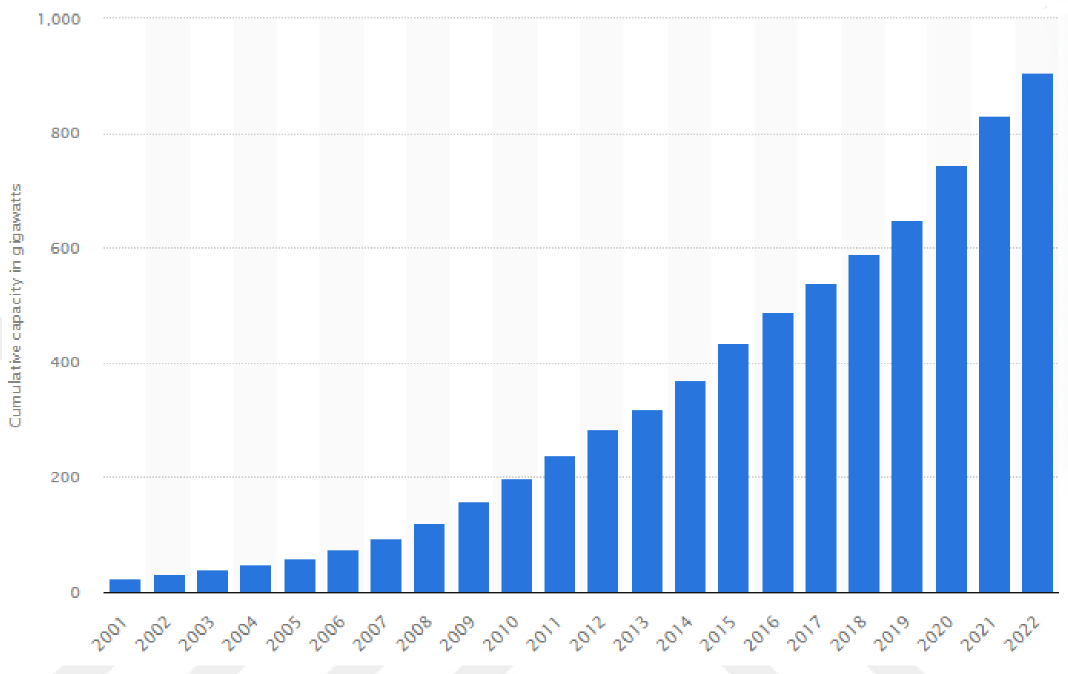

Figure 1. Cumulative capacity of the wind power installed worldwide (2001-2022).

Figure 2 depicts the total annual wind power generation in Terawatt-Hours (TWh) of the top ten countries' wind power (Wisevoter, 2023). It shows that China and United States have the highest annual wind power generation. Turkey has the lowest annual wind power generation in the graph compared to other countries. Renewable energy resources' demand is increasing as the global population expands, while meeting the climate change mitigation requires that an increasing share of energy output be based on renewable energy. According to the Renewables (2023), wind and solar power together accounted for 12% of worldwide electricity generation, maintaining an increasing trend from 2015. Approximately 326 firms had contracted a total of 77.4 Giga Watt (Liang, Wang, & Li) of energy from renewable sources, including 45 GW of solar and 28.8 GW of wind energy. Although wind power generation in worldwide is still small, it is increasing rapidly. By the end of 2022, wind power capacity was around 900. Furthermore, according to data from the United States Energy Information Administration, Denmark (44%), Portugal (26%), Spain (24%), Germany (23%) generated the most electricity from wind (Wolniak & Skotnicka-Zasadzień, 2023).

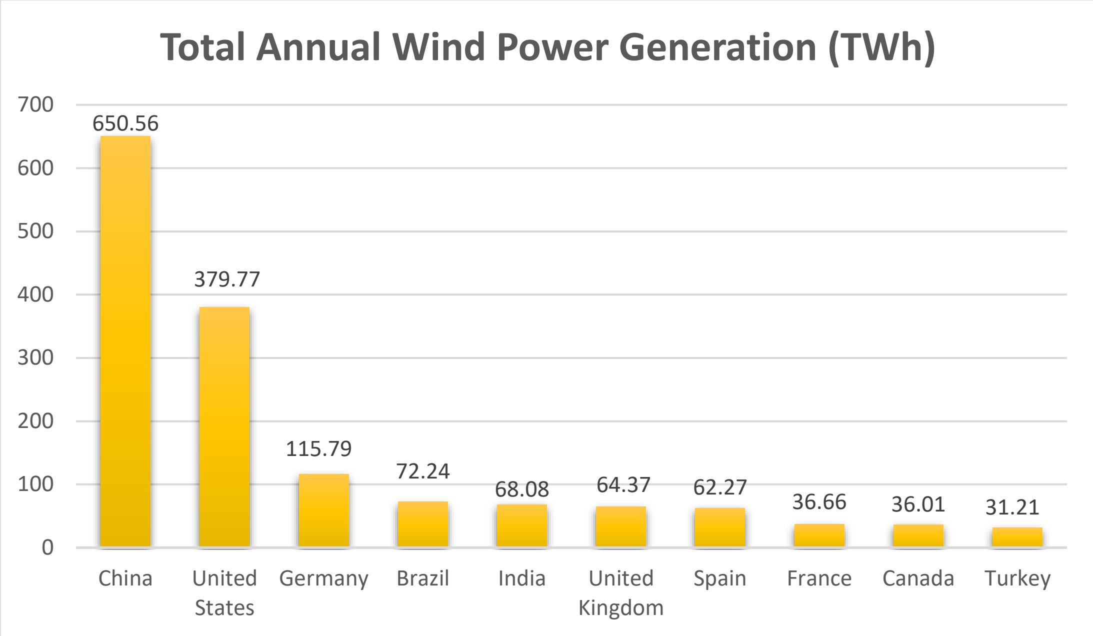

Figure 2. Country wise wind power generation.

Wind, unlike most other renewable energy sources, is inherently changing and uncertain. As a result, it is an unstable source of electrical energy, posing challenges for wind power plant and transmission system operators who require reliable data for unit commitment, dispatching, and trading in power markets. Forecasting wind behaviour has emerged as an essential subject in renewable energy research at this moment. Furthermore, accurate forecasting systems for wind power based on wind behaviour are essential for wind power plant operators to decrease the financial and technical risk of wind power production uncertainty, because differences in anticipated wind power would impact prices for both energy market and operational reserves. Improving wind power generation forecasting is difficult, not only because the outcomes are dependent on a range of factors, such as models, weather data quality, and local geographic features, but also because of insufficient empirical data.

This work aims at investigating Machine learning (ML) approaches to forecast wind power in order to improve the predictively. Primarily, the comprehensive analysis of the existing work on wind energy forecasting systems is investigated and evaluated to lay the groundwork for our research. This comprehensive analysis assisted in identifying gaps in current approaches. Secondly, this work focused on analyses two forecasting scenarios: forecasting the next hour's energy output based on data from the previous day (Case 1) and forecasting the next day's output based on data from the previous week (Case 2). This work employs the Artificial Neural Networks (ANN), Support Vector Machine (SVM)-Linear, SVM-Poly, and SVM-RBF machine learning algorithms for wind energy forecasting. A thorough analysis and comparison of these wind energy prediction models are performed using performance metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The analysis focused on training time accuracy and efficacy, giving useful insights into the strengths and limitations of each model. This work finding makes a significant contribution by exhibiting improved accuracy and efficacy in wind power generation, as well as enhancing forecasting methodologies in renewable energy.

1.1 Statement of the Problem

Wind power has emerged as an important element among renewable energy as the globe transitions to sustainable sources of energy. Despite its potential, the wind's unstable and unpredictable nature makes precise wind power generation projections difficult. This unpredictability complicates network integration and management, impacting the reliability and efficacy of wind power. The failure to accurately predict wind power results in ineffective use of wind resources. It also limits the complete incorporation of wind energy into the power grid and provides a substantial barrier to get energy supply-demand balance. The research focuses on:

- How can we enhance wind speed and direction forecasting?
- What are the most accurate models for forecasting wind power generation?

1.2 Purpose of the Study

The purpose of this study can be diverse, encompassing various main objectives that contribute to the development and optimization of wind energy systems. Here are some of the underlying objectives:

- To improve the reliability and accuracy of wind power forecasts using machine learning techniques. Machine learning algorithms can identify complicated trends in meteorological and historical wind data, resulting in more accurate forecasts of future wind energy generation. Accuracy improves the efficiency of energy planning and power grid management.
- To optimize wind energy production using machine learning techniques. Accurate projections allow for improved planning of wind energy integration into the power system, assisting in matching energy supply with energy demand and guaranteeing a steady and predictable power supply.
- To coupled renewable energy sources, such as wind power, into conventional energy infrastructure. Machine learning forecasting models are critical in guaranteeing a reliable and steady energy supply.

1.3 Structure of the Study

This research work is structured into six chapters as shown in Figure 3. Chapter 1 gives the introductive detail and background of this research work. Chapter 2 discusses the existing work regarding the wind power forecasting domain. For instance, wind power forecasting techniques such as physical and statistical models, AI- based models, and hybrid models are discussed in detail. In addition to that, wind power dataset and time-scales of wind forecasting are also investigated. Chapter 3 provides the detail methodology of implemented models which includes SVM and ANN with considerations. Chapter 4 discusses the results and findings. Chapter 5 provides the conclusions with future directions.

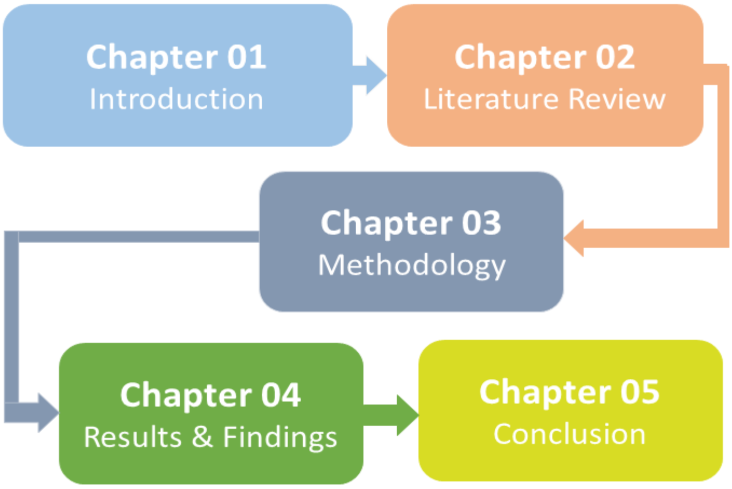

Figure 3. Thesis's outline.

Chapter 2

Literature Review

The need to utilize renewable energy sources is highlighted by the recent increase in crude oil prices, wind power in particular stands out as a highly effective and low-pollution technology. Power systems are faced with difficulties due to wind power generation's changeable nature, which is influenced by wind speed and atmospheric meteorology (Wu et al., 2022). Unexpected changes could increase operational expenses of the power supply. Power system operators must forecast fluctuations in wind power generation in order to schedule and manage spinning reserve capacity as well as the power grid to overcome these difficulties. Reducing reserve capacity and boosting wind power penetration depend on accurate wind speed predictions. Forecasts for wind power also affect energy trading, conventional power plant scheduling, and power balance (Peiris, Jayasinghe, & Rathnayake, 2021). Even though wind power projections are less accurate than load forecasts, they are nevertheless very important for addressing operational issues with the delivery of electricity.

It is theoretically possible to categorize wind power forecasts according to either applicable methodology or temporal frames (X. Wang, Guo, & Huang, 2011). The prediction of the wind power can be classified into two categories based on varying time scales: short-term scenarios, where the range of predictions is typically less than 30 minutes, and long-term projections, which have been steadily increasing over the last ten years. Conversely, the development of high-performance computer tools has aided the forecasting process, leading to the establishment of ever-newer computational techniques. In a broader sense, wind energy is essential for lowering carbon emissions from the planet, and power curves are used to gauge how successful wind turbines are. Although the dynamics of offshore wind turbines and their hostile conditions make wind power prediction difficult, precise forecasting is necessary for condition monitoring (Shabbir et al., 2022). The necessity of maintaining the grid's optimal operation presents technological obstacles that underscore the significance of reliable, long-term wind data. The necessity to meet medium and long term prediction requirements including certainity, speed, and reliability, makes the more accurate predictions difficult. These challenges' interconnectivity demonstrates how difficult it is to generate wind energy for a future that is environmentally friendly. (Tarek et al., 2023).

2.1 Related Datasets

The wind data contains the information which is collected and analysed in relative to wind turbine power generation. It contains various features related to the wind power generation such as speed of the wind, wind direction, their variations, and the efficiency of turbines and energy output. It is used for variety of purposes including optimizing wind farm operations, determining viable locations for new installations, and stability of wind power. In order to enhance and improve prediction accuracy of the wind energy forecast models, diverse datasets and consideration of their various aspects are significant. Wind power forecasting models is heavily depends on the quality of datasets encompassing meteorological conditions, historical wind patterns, and a wide range of environmental variables. Wind energy has seen an increase in popularity in recent years.

In wind power forecast models, meteorological datasets are commonly used to train the models. They provide critical information on atmospheric elements which are helpful in capturing wind patterns. These datasets provide current and predicted atmospheric conditions in real time. These datasets have information about the atmospheric condition, including wind direction, speed of the wind, temperature, humidity, and other essential data. This information is obtained from satellite observations, on-the-ground station, and complex mathematical weather prediction models, are used as an inputs for forecasting algorithms (Mandzhieva & Subhankulova, 2022). The accuracy of meteorological data have a significant impact on the precision of wind energy forecasting.

Another data that is used in forecasting models for predicting wind power is historical wind data. It contains the various features such as previous wind speed and direction trends, revealing important information about the historical evolution of wind resources. It is collected over a certain time period. It provides a historical context for assessing long-term trends, seasonal variations, and recurring patterns. (He et al., 2022). Investigating the collection, processing, and use of historical wind ML and AI technologies boost forecasting capabilities by relying on different datasets to train and modify algorithms for higher accuracy and reliability in forecasting future wind power statistics becomes critical in understanding contextual dynamics and enhancing forecasting model resilience.

Wind power data contain the wind speed, direction of the wind, output power of wind turbines, and atmospheric conditions. Wind power data is used for different objectives such as analyzing the operation of wind farms, optimization of wind turbine operations, performing research on wind energy future prospects and developing wind power forecasting models. In the context of developing wind energy forecasting models different existing studies considered the different dataset aspects. Table 1 provides the dataset aspects consideration in various existing studies.

2.2 Forecasting Wind Power with Respect to Time-Scales

Numerous wind power forecasting methods, categorized based on time-scales or methodology, are prevalent in the literature (E. Zhao, Sun, & Wang, 2022). Although the classification of time-scales in various descriptions may differ, a synthesis of literature suggests three primary categories for forecasting of wind power.

1. Short-term
2. Medium-term
3. Long-term

Table 2 provides a summary of categories of forecasting wind energy with respect to time scale. Wind power forecasting techniques can be further subdivided into physical and statistical, machine learning and intelligent, time series models based on applied methodology (Chang, 2014). The necessary input data, the accuracy at various time scales, and the process complexity are where they diverge.

Table 1

Dataset Aspects in Various Existing Studies.

References	Input Features	Target Feature	Data size	Frequency
(Nascimento, de Melo, & Moreira, 2023)	Speed of the wind, wind direction, temperature of the air, air humidity, and pressure,	Wind power	108 months	6hrs
(Ateş, 2023)	Average of ambient temperature, average of ambient speed of wind, rotor speed average, and absolute average of ambient wind direction	wind power	1 month	1hr
(Shabbir et al., 2022)	Wind speed, weather information, wind direction, ambient temperature, surrounding humidity, etc.	Wind energy	86 months	1hr
(Pelletier, Masson, & Tahan, 2016)	Intensity of turbulence, Wind direction and density of air, wind shear	Wind energy	12 months	10 min
(Mohammed & Ahmed, 2023)	Speed of the wind, wind direction,, air temperature, humidity of air, air pressure	Wind energy	Not mentioned	24hrs
(Matip, Essiane, Ngoffe, & Mougang, 2022)	Wind speed, form factor and scale factor	Wind power	12 months	24hrs
(Puri & Kumar, 2022)	Speed of the wind, temperature of air, air density	Wind power	30days	12hrs
(Jyothi & Rao, 2016)	Speed of wind, direction of air and density of air	Wind energy	15 days	10 min
(De Giorgi, Ficarella, & Tarantino, 2011)	Temperature , relative humidity, direction, and speed of the wind	Wind energy	12 months	60 min
(Mabel & Fernandez, 2008)	Wind direction, humidity level, and generation hour	Wind energy	36 months	Not mentioned
(S. Zhang & Yang, 2015)	Temperature, relative humidity, direction, and speed of the wind	Wind energy	6 days	15 min

Table 2

Wind Energy Forecasting with Respect to Time Scale.

Time scale	Range
Short-term	Next hour Prediction based on pervious 1 day data.
Medium-term	Next day Prediction based on pervious weekly data.
Long-term	Next week Prediction based on previous monthly data.

2.3 Wind Power Forecasting Techniques

A number of methods, including machine learning, statistical modelling, and physical modelling, have been documented in the literature to increase the prediction accuracy of wind power generation (Hossain, Chakrabortty, Elsawah, & Ryan, 2021). The mathematical models used in the physical and statistical models are imprecise, and their incapacity to adjust and learn results in increased prediction mistakes (Hossain et al., 2021). Machine learning techniques offer more accurate forecasting by reducing errors. They fall into two categories: deep learning models and conventional models. K-nearest neighbours, SVM, ensemble models, Bayes learning, and neural networks (NNs) are examples of conventional models. Although the accuracy of these models' forecasts has increased, their inability to extract deep-level features without specialist feature engineering prevents them from correctly relating input and output data (Hossain et al., 2023).

Based on variations in modelling philosophy, forecasting models can be categorized into four groups: hybrid models, AI-based models, physical models, and classic statistical models. This classification draws attention to the variety of methods used in the field of wind power generation prediction and emphasizes the continuous research and development of techniques to maximize forecasting model accuracy and efficiency. Figure 4. The summary forecasting models provides the comparative summary of wind energy forecasting models for quick glance. Existing work related to these models is summarized in Table 3.

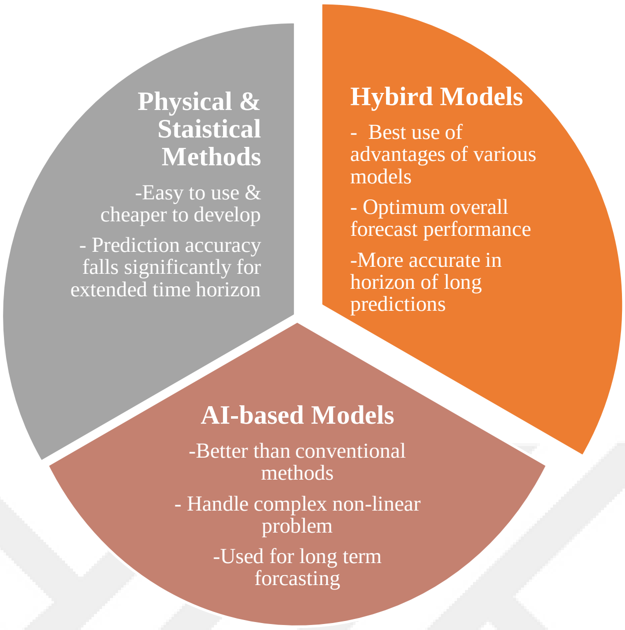

Figure 4. The summary forecasting models for wind energy.

2.3.1 Physical and statistical techniques. Physical techniques and models are conventionally used for forecasting wind energy. They considers the numerical weather estimations and depends on dynamical models of air flows to determine wind speed at the hub height for the given location. Based on obtained wind speed, forecast of the resultant wind power output is obtained. In order to forecast the wind speed, the these models often considered various features including temperature, humidity, air pressure, and historical wind speed time series (Jung & Broadwater, 2014). Over the years, various physical methods have been proposed. WRF (Weather Research and Forecasting) and NWP (Numerical Weather Prediction) (Hu, Heng, Wen, & Zhao, 2020) are the most commonly used. It is stated that these models more effective in case of medium- and long-term wind speed predictions. The downscaling techniques is introduced into these models so that area roughness, temperature, pressure, and barriers can be incorporated.

The statistical data from the Numerical Weather Prediction (NWP) is considered in complex mathematical models to produce the wind speed (Jung & Broadwater, 2014). Authors in (Hu et al., 2020) stated that physical models have the better performance in case of medium and long term Wind speed (WS) forecasting. The work in (Y. Wang, Zou, Liu, Zhang, & Liu, 2021) employed the power curve of wind turbine in order to Wind Power (WP) forecasts. Focken, Lange, and Waldl (2001) proposed the physical forecasting technique that can be used 48 hours in advance. The work in (Shahram Hanifi, Liu, Lin, & Lotfian, 2020) considered that various factors such as number of variables, including geography and daily fluctuations in air thermal stratification for predicting wind speed at hub height based on weather forecasting.

Statistical analysis is very helpful in determining the linear and non0linear correlation between wind power and the data features. Shahram Hanifi et al. (2020) proposed a model using real time power and historical data which have potential to forecast the wind power generation for the next few hours. The integration of statistical and physical techniques highlights the complexity of recent developments in wind power forecasting models. The work in (Rajagopalan & Santoso, 2009) used the wind speed as the input feature for the Autoregressive Moving Average (ARMA) approach with an hourly and thirty-minute sample rate. Dowell and Pinson (2015) considered that the Vector Autoregressive (SVAR) method with a higher frequency sample rate of five minutes and used wind speed as an input feature. Another approach is presented by Karakuş, Kuruoğlu, and Altınkaya (2017) used wind speed as the input feature and an hourly sampling rate to implement the Power Autoregressive (Park, Jung, Lee, & Hur) technique.

2.3.2 Intelligent techniques. Intelligent techniques such as deep learning and machine learning are emerging technologies that are used to increase wind power prediction accuracy. These techniques have great potential for identifying the complicated patterns in the data. Intelligent based techniques provide increased adaptability and suitability for various complicated datasets. However, in such techniques, the tuning the parameters and optimization is a challenging. These techniques necessitate significant computational resources for their operation (Tawn & Browell, 2022).

Authors in (E. Zhao et al., 2022) employed intelligent techniques to achieve accurate high-frequency wind energy forecasting outcome. These techniques are quite facilitating in the design of a more accurate and flexible forecasting framework by coupling the dynamic algorithms and real-time data. This is an emerging field that can optimize renewable energy supplies and address the difficulties of wind patterns.

Li, Zhao, Tseng, and Tan (2020), proposed the SVM-based strategy coupled with the improved Dragonfly Algorithm. The authors stated that the proposed SVM strategy have the better performance compared to other bench mark models like Gaussian process regression and Back Propagation NN (BPNN). Furthermore, Yildiz, Acikgoz, Korkmaz, and Budak (2021) developed the deep transfer learning based model which performed better than bench mark models: CNN and LSTM. After a thorough analysis and evaluation of four machine learning methods ANNs. The work in (Buturache & Stancu, 2021) proposed a novel technique based on the integration of Spatiotemporal Correlation Modelling (STCM) with CNN-LSTM. Buturache and Stancu (2021) concluded that the proposed novel approach has the lowered error metrics for extreme short-term predictions, as compared to CNN and LSTM models. The proposed STCM improved the accuracy of wind power forecasts by addressing spatiotemporal correlation. From the literature analysis, it is observed that the integrating machine learning, deep learning, and intelligent techniques helps in significantly improving the accuracy and versatility of wind power forecast models. This integration will lead to that more efficient wind energy systems is used to produce sustainable electricity.

The work in (Lin & Liu, 2020) implemented the ANN based model for forecasting wind power because they have the capability to determine the non-linear relationships between input factors and output data. In ANN base models, architecture consisting of input, hidden, and output layers. The model is trained to update and tuned the parameters of the model so that present patterns in the data can be efficiently learned for favourable outcome. Lin and Liu (2020) employed ANN model to get complex trends in the data for forecasting wind power. Various factors such as data preparation, data structure, learning strategy, relationships between input and output data, and more, can affect the performance ANNs (Marugán, Márquez, Perez, & Ruiz-Hernández, 2018). A Wavelet Neural Net (WNN) that couples the wavelet transform with a transformer-based deep neural network approach is proposed for predicting wind generation of wind power for the next six hours using a variety of meteorological parameters as input for time series forecasting (Nascimento et al., 2023; J. Wang, Yang, Du, & Niu, 2018). The ANN model and the WNN model were evaluated in the study by (Mohammed & Ahmed, 2023) to see which is better suited for wind speed forecasting. Some other approaches include BPNN, Radial Basis Function NN (RBFNN) (Sideratos & Hatziargyriou, 2012), Elman NN, (ENN), etc (De Giorgi et al., 2011). Choosing the right network topology and determining the information flow direction are the two main tasks involved in designing ANNs. There are two main topologies: recurrent for mutual directions and feed-forward for data moving in one direction from the input to output layers. Selecting the appropriate learning algorithm from supervised, unsupervised, and reinforcement learning is the second stage.

For the purpose of predicting short wind power, Jyothi and Rao (2016) employed an adaptive WNN. They were able to attain a minimum Normalized RMSE (NRMSE) of 0.02. Four distinct wind farms' wind power was predicted using a Multi Layered Perceptron (MLP) network. They assessed several combinations of wind direction, air temperature, humidity, and sun radiation as input variables, even though wind speed is the main input for their model. Apart from wind speed, the results showed that air temperature had the greatest impact on improving the model's accuracy. The authors considered log-sigmoid transfer as the activation function and the Levenberg-Marquardt backpropagation method as the best structure for MLP.

The MLP with the lowest Normalized Mean Square Error (NMSE) was found to have three hidden layers with five, seven, and eight neurons in each hidden layer. A single 15 kW wind turbine on a Chinese west wind farm was examined using ENN. Using the input features of air temperature, humidity, wind direction, and speed, the authors showed good accuracy (S Hanifi, Liu, Lin, & Lotfian). This accuracy was particularly noticeable once the particle swarm optimization method was used.

2.3.3 Hybrid approach. Hybrid approaches are those that coupled various forecasting techniques. Fuzzy logic models and artificial neural networks are two examples of hybrid systems that incorporate several forecasting methodologies (Hong & Riofloriido, 2019). Hybrid techniques can potentially couple the strengths of the various techniques in order to increase the overall accuracy. In machine learning and data science, numerous methods and training datasets are often employed to generate a range of predictive models. Ensemble modelling is a term used to describe this approach, which is a more advanced form of hybrid forecasting. In terms of performance comparison of combination components, hybrid techniques might not always yield superior results. However, research has shown that these methods are generally superior (Jung & Broadwater, 2014). Several hybrid approaches that include multiple models have been put out, indicating the continuous progress in wind energy forecasting. These initiatives range from the integration of machine learning methods to the combination of physics-based and data-driven models.

For example, academics are investigating novel ways to combine machine learning algorithms with numerical weather prediction models to better use various forecasting methodologies. These hybrid models benefit from improved input data quality thanks to the integration of sophisticated sensors, satellite data, and real-time monitoring systems. By taking into consideration geographical characteristics, atmospheric variables, and temporal variability, this interdisciplinary approach seeks to address the dynamic and complex nature of wind energy systems.

Hybrid solutions for wind energy forecasting are emerging as technology progresses and new paradigms such artificial intelligence and self-learning algorithms are adopted. Further study is required to increase the accuracy of forecasting models in order to maximize energy output, preserve grid stability, and facilitate the transition to sustainable, renewable energy sources. Table 5 provides an overview of some of the hybrid approaches literature. (Hong & Rioflorido, 2019) proposed a hybrid CNN-based wind power prediction model with features collected via kernel, convolution, and pooling. Using an RBFNN as the activation function, the model used the Double Gaussian Function (DGF). Adaptive moment estimation (ADAM) was used to enhance the concept. Based on historical power data from a wind farm in Taiwan spanning a year, the concept outperformed previous approaches in wind power forecasting. THANGARAJ, Tamizharasi, and Muthukumaran (2023) presented a MLP based approach to improve the performance of the power generation forecast by estimation of the wind speed with improved accuracy using average temperature of the air, relative humidity, and vapour pressure data.

For wind power forecasting, Lima, Guetter, Freitas, Panetta, and de Mattos (2017) utilized a hybrid model that included statistical and physical methods. The model used polynomial regressions and a Kalman filter to remove systematic errors before coming to the conclusion that cubic regression produced the best results. Through lowering RMSE, increasing anomaly correlation, and improving Nash-Sutcliffe coefficients, the Kalman filter increased forecasting accuracy. For reliable wind power forecasting, Lin, Liu, and Collu (2020) combined isolation forest with a deep learning neural network. This method was especially useful for handling non-normally distributed data.

For wind power forecasting 1-6 hours in advance, Y. Zhao et al. (2016) suggested a bidirectional model that outperformed forward, backward, and persistence techniques. J. Liu, Wang, and Lu (2017) demonstrated better accuracy than individual models when they coupled Least Square Support Vector Machine (LSSVM) with BPNN and RBFNN through an Adaptive Network-based Fuzzy Inference System (ANFIS) for 48-hour forward forecasting of the wind power. A multilayer feed-forward NN was utilized by (P. Zhao et al., 2012) to increase predicting accuracy by reducing systematic errors in wind speed from a meteorological research and forecasting model using a Kalman filter.

Through creative hybrid models and methodology, each of these studies advances the field of wind power forecasting by demonstrating a variety of ways to improve the precision and dependability of wind energy production predictions.

Table 4 analysed the existing short-term forecasting performance in terms of performance metrics such as MAE, MSE, RMSE, etc. It can be observed that different studies proposed that different model and evaluated it.

Table 5 analysed the existing medium-term forecasting performance in terms of performance metrics such as MAE, MSE, RMSE, etc. It can be observed that different studies proposed that different model and evaluated it.

Table 3

Summary of Recent Existing Work.

Reference	Model	Approach	Performance Metric
(Ateş, 2023)	ANN with Particle Swarm Optimization	Short term	MAPE=5.6956
(Ponkumar, Jayaprakash, & Kanagarathinam, 2023)	Random Forest	Short term	MAE=2.34, MSE= 27.94, RMSE= 5.28
(Margarat, Kumar, & Rajan, 2023)	ANN	Not mentioned	MSE=2.63,RMSE=2.68
(Nascimento et al., 2023)	Transformer-based deep neural network.	Medium term	Mean RMSE=1.5871, Mean Pearson's r correlation=0.7393, Mean Fac2 =0.9772.
(Margarat et al., 2023)	SVR-Random Forest Regression (RFR)	Not mentioned	MSE= 1.67, RMSE= 1.69
(Y. Wang et al., 2023)	Wavelet network with teacher forcing	Short term	MAE=10.74, MSE=199.81,
(Wen, Pinson, Gu, & Jin, 2023)	Fully conditional specification	Short term	RMSE=0.281
(Z. Zhang, Wang, Wei, Luo, & Xia, 2023)	Ensemble Model	Short term	MAPE =6.71%
(Salb et al., 2023)	LSTM couple with Sine-Cosine Algorithm	Long term	MAE=0.050028, MSE= 0.005046, RMSE=0.071035
(L. Liu et al., 2023)	Deep Bayesian model	Short Term	MAE=0.057, MAPE=19.58%
(Park et al., 2023)	Gradient Boosting Regression	Short Term	Normalized MAE=0.515
(Xiang, Liu, Yang, Hu, & Su, 2022)	Self-attention temporal CNN based on LSTM	Short term	RMSE=0.680, MAE=0.546

Reference	Model	Approach	Performance Metric
(Y. Zhang & Wang, 2022)	Elman neural network with PSO	Short term	RMSE = 0.6110, MAE = 0.4883, MAPE 12%
(Shabbir et al., 2022)	RNN-LSTM	Short term	RMSE =13
(Ağbulut, 2022)	Variance sensitive exponential smoothing model	Short term	MSE=0.183, MAPE=14.60%, RMSE= 0.427

Table 4

Performance Analysis of Existing Short-Term Forecasting.

Reference	Model	Performance Metric
(Ateş, 2023)	ANN with PSO	MAPE=5.6956
(Ponkumar et al., 2023)	Random Forest	MAE=2.34, MSE= 27.94, RMSE= 5.28
(Y. Wang et al., 2023)	Wavelet network with teacher forcing	MAE=10.74, MSE=199.81,
(Wen et al., 2023)	fully conditional specification	RMSE=0.281
(Z. Zhang et al., 2023)	Ensemble Model	MAPE =6.71%
(L. Liu et al., 2023)	Deep Bayesian model	MAE=0.057, MAPE=19.5%
(Park et al., 2023)	Gradient Boosting Regression	Normalized MAE=0.515
(Xiang et al., 2022)	Self-attention temporal convolutional network based on LSTM	RMSE=0.680, MAE=0.546
(Y. Zhang & Wang, 2022)	Elman neural network with PSO	RMSE=0.611, MAE=0.488, MAPE=12%
(Shabbir et al., 2022)	RNN-LSTM	RMSE=13
(Ağbulut, 2022)	Variance sensitive exponential smoothing model	MSE=0.183, MAPE=14.60%, RMSE=0.427
(Xiong, Guo, Zeng, Zou, & Wang, 2022)	SVM	MAE= 9.02, RMSE=11.74

Table 5

Performance Analysis of Existing Medium-Term Forecasting.

Reference	Model	Performance Metric
Trabelsi, Mimouni, & Shatanawi, 2022)	ANN	NMAE=0.04, RMSE=0.0205
(Nascimento et al., 2023)	Transformer-based deep neural network.	RMSE=1.5871, Pearson’s r correlation=0.7393, Fac2=0.9772.
(Jamii, Mansouri, Trabelsi, Mimouni, & Shatanawi, 2022)	Least Absolute Shrinkage and Selection Operator (LASSO)	NMAE=0.069, RMSE= 0.0434
(Xiong et al., 2022)	SVM	MAE=9.02, RMSE=11.74
(Barbosa de Alencar et al., 2017)	ARIMA	MAE=1.135, RMSE=3.590
(Barbosa de Alencar et al., 2017)	NN	MAE=0.345, RMSE=1.091

Chapter 3

Methodology

This chapter provides the detailed explanation of dataset used and the methodology that is followed to implement our models ANN and SVM for wind power forecasting. It explains the architecture of both models and how they are modeled to predict wind power.

3.1 Undertaken Dataset

The dataset which is considered in this research, cover the period from October 17, 2012, to January 1, 2014, with recordings every ten minutes, provides a detailed temporal snapshot of vital atmospheric variables for wind energy analysis. In the wind power generation forecasting dataset, various meteorological input features are crucial in predicting the target value of wind energy output measured in Watt-hours (Wh). Speed of the wind, measured in meters per second (m/s), is the most direct indicator, as it fundamentally influences the kinetic energy available for conversion into electricity by wind turbines. Wind direction is also important because it influences the efficiency of turbine blades in catching wind energy; certain wind directions may match better to the fixed direction of some turbines, influencing power generation. The quantity of kinetic energy in the wind can be affected by temperature, which is measured in degrees Celsius (C). Humidity, or the quantity of moisture in the air, can also play a role since it influences air density and can cause corrosion or other mechanical faults in turbines, reducing performance. When combined, these characteristics provide a comprehensive collection of predictions that, when processed using machine learning algorithms, enable precise forecasting of wind power generation, assisting in efficient energy scheduling and grid management. This dataset is useful for designing accurate and adaptive forecasting models for wind energy that incorporate short-run fluctuations to maximize wind energy utilization.

3.2 ANN Architecture

The ANN design as shown in Figure 5, is used to predict wind power using wind data inputs and a multiple-stage framework. It comprises of three main layers: input, hidden, and the output. The input layer nodes receives the wind power data from the outside world and weighted sum is calculated to pass data to the hidden layer. The weighted input sum can be calculated as follows:

$$\sum_{i=1}^{n} W_i \times X_i + b \tag{1}$$

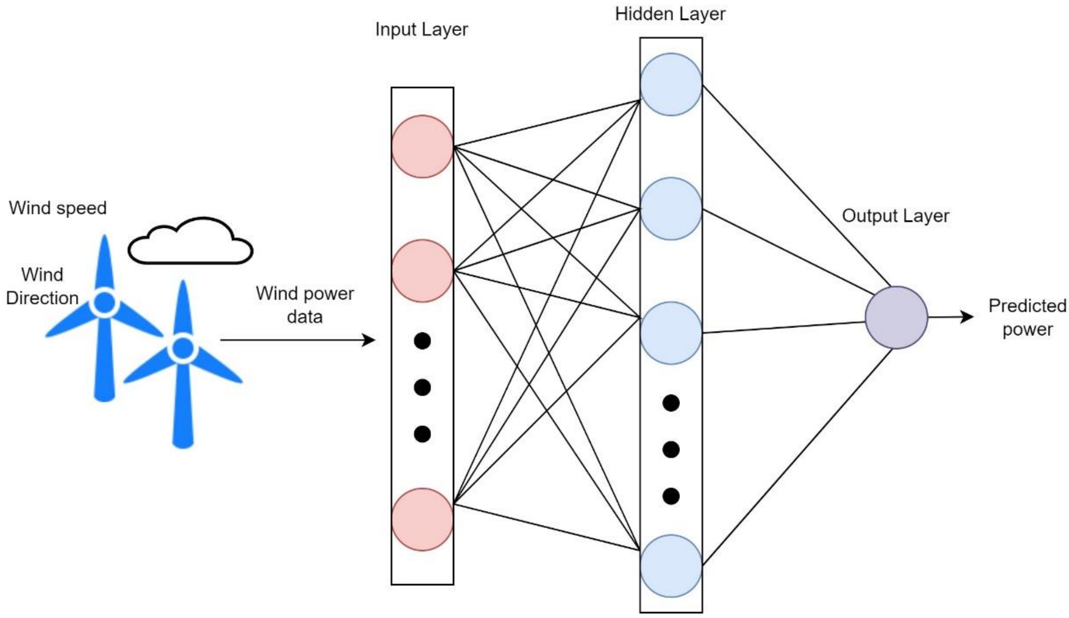

Figure 5. ANN architecture for forecasting the power.

The result of the given equation is processed using an activation function, such as ReLU, or sigmoid, among others. The activation function converts the node's summed weighted input into a value that can be passed to the hidden layer or used as the final output. The hidden layer nodes compute and process the input data. The outputs of the layers that were previously hidden serve as the inputs for the incoming layer. A complex web of interdependencies is formed within the neural network architecture by each neuron creating biased and weighted connections with every other neuron in this interconnected structure.

Figure 6 shows a structured approach to training a neural network model. Initially, data is pre-processed to prepare it for input into the model. The network is then initialized with initial weights and biases, after which the training parameters, such as the number of epochs and learning rate, are set. An optimization algorithm is initialized to facilitate efficient network parameter updates during training. The model undergoes forward propagation to calculate the predictions, followed by

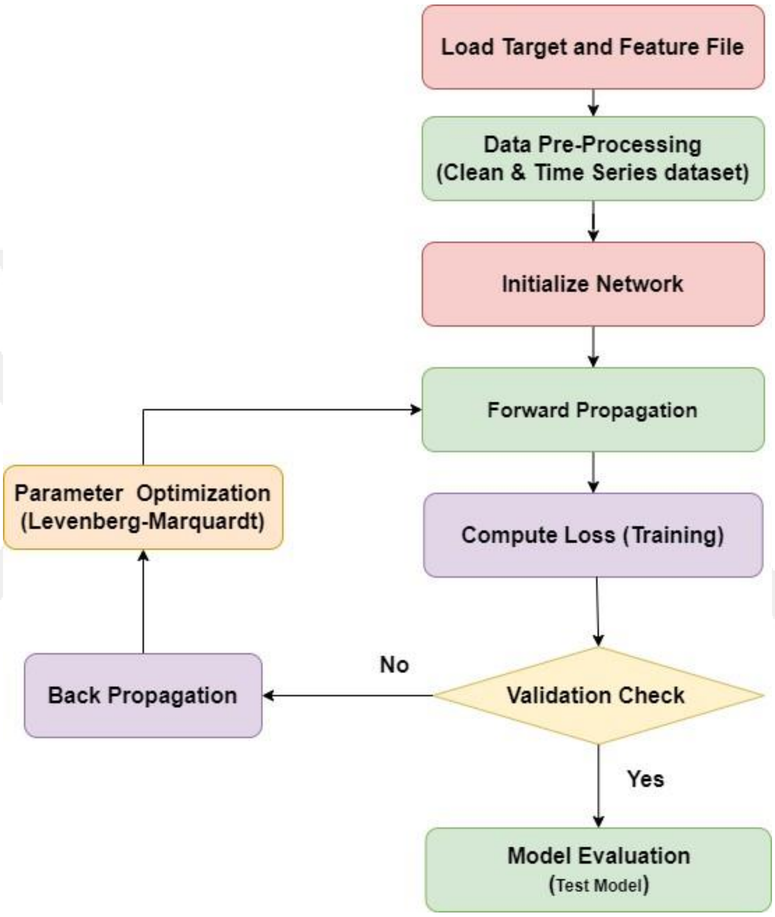

Figure 6. ANN model's flow chart.

backpropagation to compute the gradients based on the difference between the predicted and actual values. Afterwards, the optimizer updates the network parameters using these gradients. The model's performance is assessed by computing the loss on training and validation datasets. An early stopping mechanism is employed to prevent overfitting, which monitors the validation loss and halts training if the model does not improve after a certain number of iterations. Finally, the trained model is evaluated using a test dataset to gauge its predictive accuracy.

3.2.1 Load target & feature file. The wind power data is uploaded. It is analysed for input features and target.

3.2.2 Data pre-processing. Data preparation is an important step to ensure the data's quality and effectiveness for training and optimizing the SVR model. Pre-processing of the data involves handling of missing or null values, evaluating the significance of various features and selecting or removing them with respect to their significance, deal with outliner, normalization. Missing values are checked and handled through imputation. Rows with NaNs, resulting from the lagging process, are removed to maintain data consistency. In addition, feature extraction process is performed to extract relevant and most significant features from the data. For this, correlation between each feature and the output is computed and the features with the strong correlation are selected for further processing. For normalization, min-max technique is used to avoid features with large ranges from dominating the cost function metric. Outliers are also identified and removed during the pre-processing of data so that more reliable and accurate predictive model can be developed. Modifications are applied to datasets with time-dependent patterns. By generating historical observations based on the current situation, time series data is analysed, enabling the neural network to better forecast future events and identify temporal relationships. During training, our developed strategy ensures that the network recognizes and uses temporal variations in the data.

The resulting dataset is then carefully separated into test, validation, and training sets based on predetermined ratios, with normalized features and lagged goal values. This segmentation is critical for model validation and testing, as it ensures that the ANN model is adequately trained, verified, and tested on unknown data, measuring its capability for generalization and robustness.

3.2.3 Initialize network. To initial the model, model weights, biases, and parameters, learning rate, and the total number of epochs, are define. For efficient network update of parameters during training the optimization algorithm is used.

3.2.4 Forward propagation. It is an essential element of the NN model in machine learning which has to process and propagate the input data throughout the model and calculate the model's output. The data X is mathematical process as follows:

$$\boldsymbol{Z_1 = W_1 1. X' + b_1} \tag{2}$$

In this expression, the variables W_1 and b_1 are representing the weights and biases of the first layer respectively, and X' is the transpose version of X. The activation function of Rectified Linear Unit (ReLU) is applied to its output.

The ReLU function for activation can be defined as $A = max(0, Z)$, is used to remove any negative values from Z_1 and putting them to zero and include the nonlinearity. This is process help the neural network to efficiently learn and characterize complicated patterns in the input. A_1 represents the first layer's activated output. The first layer output A_1 is utilized as the input for the next subsequent layer, which is process similarly as the first layer. It can be defined by second layer's weights (W_2) and biases (b_2) as follows.

$$\boldsymbol{Z_2 = W_2. A_1 + b_2} \tag{3}$$

This layer's output $Z_2 = A_2$ is the ultimate output from the forward propagating process. It does not use a non-linear activation function at this model is used in applications such as regression where a linear output is our interest. This propagation process that is explained is crucial for enhancing the capability of neural networks to analyse input data and produce meaningful output.

3.2.5 Back propagation. It involves the computation of gradient of the model with respect to each parameter. It is computed using ReLU activation function. The gradient of an activated input A is obtained as dA and matrix with each binary element representing one if the associated component of A is larger than zero and otherwise represents zero. This gradient computation is important in the backpropagation process because it specifies where the ReLU activation has a considerable impact on the backward processing of training procedure.

Back propagation process is an important aspect in neural network models training process, particularly in case of training an ANN model for regression applications. The backpropagation procedure is more complicated and executes the backpropagation algorithm's core. It computes the gradients required to update the network weights and biases. The activations obtained from the forward propagation$(A1, A2)$, the original input data X, the actual outcome Y, and the weights of the second layer W_2 are all fed into the process. The first step is to find the loss function gradient with respect to the network output (dZ_2). I use this gradient to determine the weights' gradients (dW_2) and biases (dZb_2) in the output layer. This gradient must be returned to the hidden layer as the next step. When you multiply dZ_2 by the second layer's shifted weights, you get an alignment (dA_1). with respect to the activation of the first layer. In order to get the loss function gradient, gradient of the ReLU function is then multiplied by this value element by element with respect to the pre-activation of the first layer (dZ_1). Then, the first layer gradients with respect to weights (dW_2) and biases (db_1) are computed.

These gradients (dW_1, db_1, dW_2, db_2) are significant for learning an ANN. They help in learning the model's parameters so that weights and biases are adjusted in order to minimize the loss function. This process is helpful in improving the model's performance during the training process. The whole model process is reiterated with different training instances and intervals, allowing the neural network to learn from the data effectively.

3.2.6 Liebenberg-marquardt optimizer. The optimization techniques are important for the optimization of the ANNs model for the purpose of forecasting wind energy. This technique help in solving a common problem in wind energy data modeling that is non-linear least squares. The Levenberg-Marquardt optimization technique is a hybrid approach that combines the strengths and resiliency of the gradient descent approach with the strengths and effectiveness of the Gauss-Newton method. This integration of two techniques helps in enabling the algorithm to be responsive to the complexity of the inaccurate landscape. In case of wind forecasting it is important as the patterns of data can be exceedingly detailed and non-linear.

The hybrid optimization approach is used in ANNs Model for wind power forecasting to navigate a complicated error surface in order to optimize network weights. It is essential for effectively modeling the complicated relation between different inputs and wind power generation. This hybrid algorithm has potential to shift from a Gauss-Newton-like approach to a gradient descent approach in case of complex error surface to make the model more efficient. It enables ANN model to effectively learn from the data, despite the presence of intricacies and unpredictability of wind patterns. The adaptability this optimization approach is crucial for swiftly determining the optimal set of parameters in the ANN, which immediately leads to more accurate and steady wind energy projections. It help in improving the ANNs' ability for dealing with the non-linear and complicated nature of wind data to reliably analyze and forecast wind power production. Utimately, it is a vital in improving the dependability and accuracy of wind energy models for forecasting.

3.2.7 Computing loss (training). It is important to calculate during training process. It computes the difference between the actual and anticipated values throughout the training phase so that the model forecasting capabilities can be enhanced based on this difference. In order to compute the training loss, MSE measure metric is used. It is the average of the squared discrepancies between the actual and projected values. The two key factors: a penalty for resulting incorrect predictions and an L2 regularization component are added to the loss function in addition to MSE measure.

The unfavourable prediction penalty is used so that wrong predictions of target output that are less than zero can be penalizes. The penalty factor is required in case of negative forecasts that can pose a larger risk. This factor guarantees that the model is biased against producing such predictions. The factor L2 regularization term is used to reduce the total of all the weights' squares by considering the model's complexity. The regularization factor is defined by parameter lambda and it help in preventing the model from overfitting and make the model capable for well generalization. This loss function with additional factors makes the neural network model that are robust, realistic, and trustworthy for accurate predictions. Overall, it enhance accuracy based on MSE value, unfavourable prediction penalty, and generalization with L2 regularization.

3.2.8 Validation check. It is used to enable early stopping of the model so that overfitting can be avoided. Early stopping of the model is a critical step in training a neural network model effectively. It consider the three factors: best-value-loss, patience, and minimum-delta

The best-value-loss is defined initially so that the validation data along with the minimal loss throughout training can be tracked. The patience factor is defined guide the model on how many training cycles are required to execute before the validation loss falls below a specific amount (min-delta, set to 0.0001). A counter called "wait" maintains track of how many epochs have transpired since the last validation loss improvement. The algorithm tests the model on training as well as validation data after modifying the network parameters with the optimizer throughout each training period. It computes the monitoring training loss and the validation loss for early stopping checks. If the current epoch's validation loss is less than best-val-loss minus min-delta (showing a considerable improvement), best-val-loss is modified to this new lower value, and the waiting counter is reset to 0. If there is no significant improvement, the wait counter is incremented. When the wait counter exceeds the patience threshold, it indicates that the model has not witnessed any significant reduction in validation loss for a set number of successive epochs. The training is over at this moment. This method gives the model sufficient time to learn and enhances generalization by terminating training at the appropriate time, resulting in successful regularization. Finally, the model that was trained is tested on a new dataset to determine its predicted accuracy.

3.3 SVM Model

SVM is a supervised machine learning algorithm that can be used for classification as well as regression. SVR is an altered variant of the SVM approach created for machine learning regression challenges. SVR has a wide range of applications, including economics for predicting the value of stocks, engineering for predicting functions, and environmental research for modelling ecological processes. It is also used in sectors such as wind power production forecasting, solar power prediction, and consumption of energy prediction, healthcare diagnosis, and weather forecasting.

SVR's basic principle of maximizing the margin between data points differentiates itself by prioritizing the prediction of continuous real-number values.

Figure 7 shows the basic architecture of the SVR. The SVR function is to transform the feature vectors of sample data from a lower dimension to a higher dimension and then perform regression analysis on them in the higher dimension using the kernel function. SVR utilizes the same fundamental concepts as SVM for classification but with slight differences.

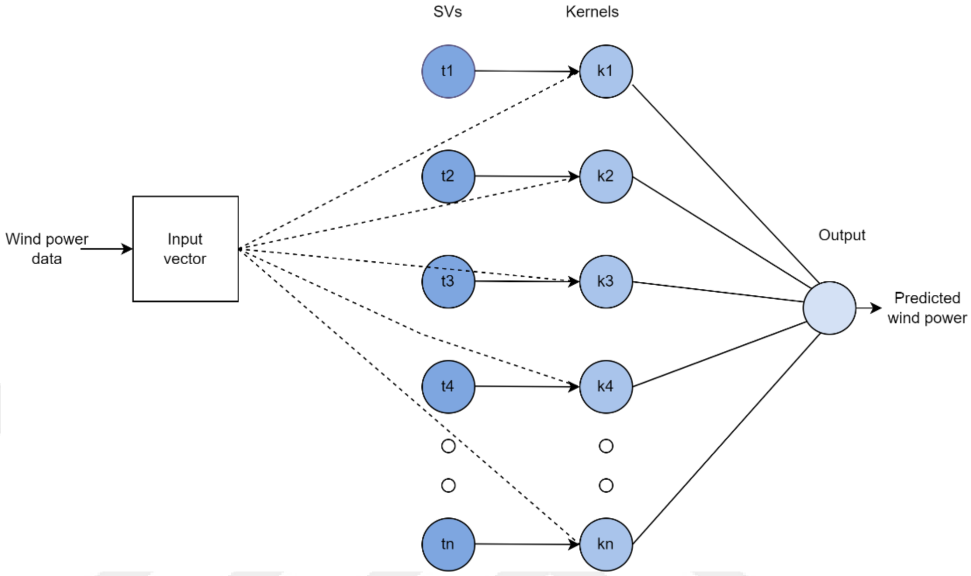

Figure 7. SVR basic architecture.

In regression, a tolerance margin epsilon is established to approximate the SVM, which has already been defined for classification. The approach operates by

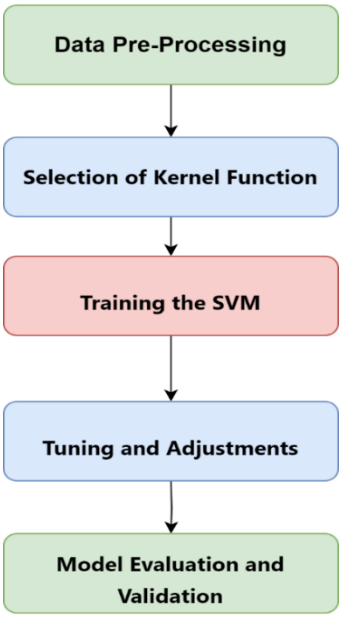

Figure 8. Flow chart of the SVM model.

identifying the hyperplane that most accurately aligns with the data, and it can be extended to address nonlinear regression problems through kernel functions. Kernel functions map the data into a feature space with a higher dimensionality, allowing the identification of a linear separation. SVR is highly advantageous for accurately forecasting continuous values inside a nonlinear framework.
Figure 8 shows the flow chart of our SVM model which contains the following steps:

3.3.1 Data pre-processing. Data preparation is an important step to ensure the data's quality and effectiveness for training and optimizing the SVR model. Pre-processing of the data involves handling of missing or null values, evaluating the significance of various features and selecting or removing them with respect to their significance, deal with outliner, normalization. Missing values are checked and handled through imputation. In addition, feature extraction process is performed to extract relevant and most significant features from the data. For this, correlation between each feature and the output is computed and the features with the strong correlation are selected for further processing. For normalization, min-max technique is used to avoid features with large ranges from dominating the cost function metric. Outliers are also identified and removed during the pre-processing of data so that more reliable and accurate predictive model can be developed.

3.3.2 Selection of kernel function. The kernel choice depends on the data's aspects and the complexity of the problem. Determine how the data is transformed before the SVM algorithm is applied. Understanding different types of kernel functions is critical to choosing the right one for a specific problem. For this problem, three kernel functions are implemented: Radial Basis Function (RBF), Linear, and Polynomial (Poly). Impact of these three kernels on SVR is investigated.

3.3.2.1 Radial basis kernel. The RBF kernel, often called the Gaussian kernel, is frequently used in SVR to capture complex and non-linear relationships. It transforms the input features into a space with infinite dimensions. The RBF kernel is shown in Figure 9. The RBF kernel is mathematically represented as:

$$\boldsymbol{K}(\boldsymbol{x},\boldsymbol{x}') = \mathbf{exp}\ (-\boldsymbol{\gamma}||\boldsymbol{x}-\boldsymbol{x}'||\mathbf{2}) \qquad (5)$$

Here, x and x' are two input feature vectors, and γ (gamma) is a parameter that determines the spread of the kernel. A larger gamma makes the model more sensitive to the training data (higher variance and lower bias), while a more minor gamma results in a smoother decision surface.

The main features of RBF are particularly efficient for addressing non-linear issues. Proficient in analyzing complex data patterns. Computationally intensive when

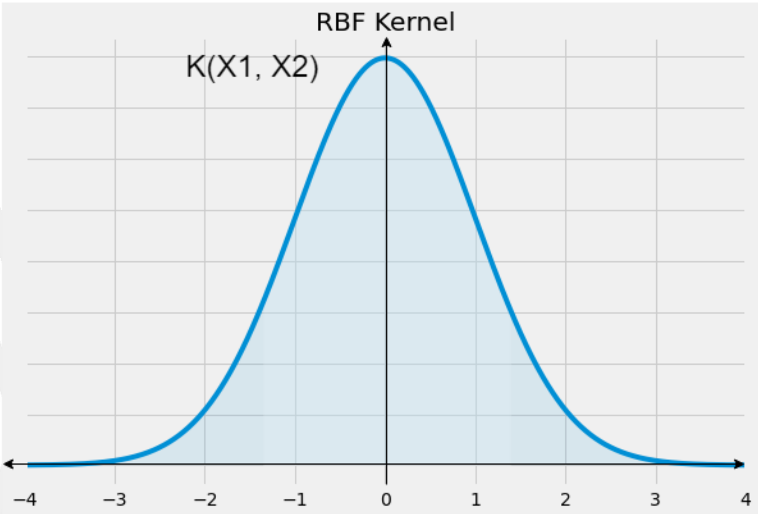

Figure 9. RBF kernel.

dealing with massive datasets. Prone to being impacted by the gamma parameter, requiring precise adjustment.

3.3.2.2 Linear kernel. The linear kernel is the simplest in SVR, ideal for linearly related data. It is often used when the relationship between the features and target variable is assumed to be linear. The linear kernel is shown in Figure 10 and defined as follows:

$$\boldsymbol{K(x,x') = x.x'} \tag{6}$$

The key characteristics of the linear kernel function are that it is computationally efficient, particularly for a large number of features, less prone to overfitting compared to RBF and polynomial kernels, has No additional parameters to tune like gamma in RBF and is limited to linear relationships, not suitable for complex, non-linear datasets.

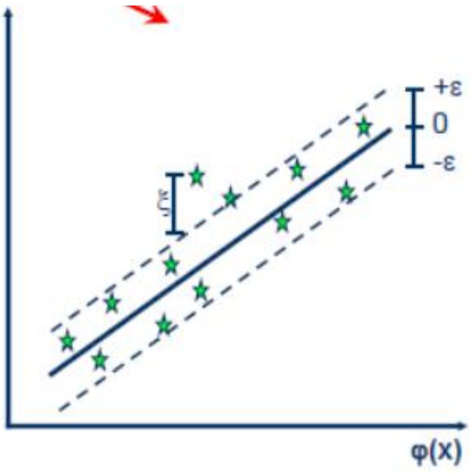

Figure 10. Linear kernel.

3.3.2.3 Polynomial kernel. The polynomial kernel allows SVR to model non-linear relationships more flexibly than the linear kernel but is typically less complex than the RBF kernel. It is expressed as:

$$\boldsymbol{K(x, x') = (1 + x.x')d} \tag{7}$$

In this formula, *d* represents the degree of the polynomial, a hyper parameter that determines the complexity of the model.

The key benefits are more versatile than the linear kernel, capable of modelling both linear and non-linear relationships, the degree *d* significantly affects the model's performance and complexity, higher degrees can lead to more complex models and risk of overfitting and it requires more computational resources than the linear kernel. However, it can be less demanding than the RBF kernel.

The kernel function in SVR is of the highest significance since it significantly impacts the model's performance, particularly when capturing the fundamental patterns of the dataset. Experimenting with various kernels and optimizing their settings is often recommended to see which produces the most optimal results for the specific regression challenge.

3.3.3 SVM model training. In order to determine the best-fitting model, SVR performs an optimization. The intent is to find a function that deviates from observed wind power generation responses by no more than epsilon (ε) for as many points of training as possible while maintaining the model as flat as possible. A fundamental component of SVR is the epsilon-insensitive loss function. This makes the model more susceptible to errors in a given range, as determined by the epsilon parameter. The following is the mathematical equation that describes the epsilon-insensitive loss function:

$$\boldsymbol{\mathcal{L}\epsilon(X, x) = \max(0, |X - x| - \varepsilon)} \tag{8}$$

Lϵ(X, x) represents the loss for a given predicted and actual values. The threshold parameter is. If the total variation between the anticipated and actual numbers is less than the margin, the loss is zero. If the difference is greater than, the loss is proportionate to the amount it beats epsilon. *Rϵ(x)* is the mean of the epsilon-insensitive loss throughout the data distribution. It is provided by:

$$\boldsymbol{R\epsilon(x) = \mathrm{E}[\mathcal{L}\epsilon(X, x)]} \tag{9}$$

This expectation shows the model's average performance across all potential data distribution values. The main principle behind the loss function is to overlook errors that are less than the threshold. This signifies that the SVR model penalizes no predictions within the tube surrounding the actual values. This property makes the model resilient to anomalies and non-Gaussian noise. The model is less sensitive to noisy data because slight deviations (within ε) from the actual values are ignored. The model is designed to minimize greater errors, which are deemed more significant. This strategy frequently results in a model which generalizes well. In SVR, the epsilon-insensitive function of loss is a valuable tool that contributes to the model's resilience and generalizability, particularly in cases involving outliers or non-Gaussian noise. SVR detects critical data points known as support vectors throughout the training phase. These sites are located outside of the tube. A regularization parameter in the model controls the balance between the model's bias and the level to which variations are more significant than are permitted.

3.3.4 Tuning & adjustments. Model tuning, called hyper parameter optimization, is a critical step in the SVM algorithm. It involves adjusting the model's hyper parameters to find the best possible model for a given problem. The SVR process is essential due to the sensitivity of the model's performance to its hyper parameters. Determines how data is mapped into a higher-dimensional space. Standard kernels include linear, polynomial, and RBF. The choice of kernel affects the model's ability to handle linear or non-linear relationships. For RBF, the gamma (γ) parameter defines how far the impact of a single training example reaches. Low values refer to far, and high values refer to close. For polynomials, the degree of the polynomial is crucial because it controls the trade-off between reducing the error on the training data and decreasing the model complexity to avoid overfitting. A high value of regularization tries to fit the training data exactly as it is, while a low value highlights a smoother decision boundary. ε controls the width of the margin where no penalty is given for errors. A smaller ε can lead to a model that captures more noise in case of overfitting. Model tuning in SVR is an iterative process that requires balancing computational efficiency and pursuing the optimal model. One can significantly improve the model's accuracy and robustness by systematically exploring the hyper parameter space and using cross-validation to assess performance.

3.3.5 Model evaluation & validation. After training and tuning the model, evaluate its performance using the testing set. The performance metrics for regression include MSE, MAE and PAME, are used to assess the model's accuracy. Theses metrics help in pretty good generalization of the model to new unknown data. When the model is trained, it is used to evaluate it using the test data.

3.4 Research Limitations

The dataset used in this work is in limited size. For improving the accuracy of forecasting models, larger and more diverse dataset is essential. The limited dataset results in limiting the capability of the models to learn complicated patterns and adapt to a broader spectrum of wind power. In case of our model, the non-linear dataset is used due to this fact SVM-Linear performance degrades.

Because SVM-Linear works well in case of linear data but the wind power prediction problem has non-linear dataset with complex patterns. This problem highlights the limitation in the applicability of models such as SVM-Linear to complicated situations such as wind energy forecasting. Limited data size also have a significant impact on the performance of SVM-RBF model for wind power forecasting In the case of too small or too diverse dataset, the capacity of the model degrades to learn and generalize well which results in lowering forecasting accuracy. This constraint becomes more apparent in the process of parameter optimization. Because SVM-RBF model is sensitive to parameter changes in case of RBF kernel and the regularization parameters. These factors should be balanced for optimal performance of the model. In addition, fine-tuning of these parameters is difficult using limited dataset because the model have insufficient data to effectively detect and learn the intricacy of wind energy patterns. Because of these limitations including proper balancing and adjustment of parameter, constraints of the dataset, the SVM-RBF model is unable to function effectively and results in inaccurate forecasts of wind power generation. In case of ANN, the data limitations reduced the efficiency of ANN model too. ANN models requires huge data to model complicated and non-linear connections. But because of the small size of our data set, the ANN was unable to be effectively trained to capture the complex patterns in the wind energy data, resulting in poor performance.

Chapter 4

Findings

This chapter gives performance evaluation of various forecasting models used to forecast wind power generation so that the valuable conclusion ca be made. The performance measures such as training duration, MSE, MAE, RMSE, and MAPE are considered in order to analyse our models.

4.1 Performance Evaluation

In order to evaluate the models, following performance measures such as training time, MSE, MAE, RMSE, and MAPE are considered.

4.1.1 Training time. Training time is an important measure that reflects the model's computational efficiency. Shorter training sessions are often favoured. In MATLAB, the tic-toc function calculates the time elapsed for a certain model training and optimizing.

4.1.2 MSE. MSE is about calculating the average squared difference between the predicted wind power generation and the actual wind power generation. The small value of the MSE shows the better fit of the model to the data. The MSE can be mathematical written as:

$$\boldsymbol{MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y'_i)^2} \quad (10)$$

Where n is representing the samples number ad y_i is actual wind power generation and y'_i is estimated wind power generation.

4.1.3 MAE. MAE measures the absolute error average between anticipated and actual wind power generation. It provides a linear score that averages the absolute deviations. A lower MAE also suggests a better model performance regarding error margins. The MAE is obtained as:

$$\boldsymbol{MAE = \frac{1}{n}\sum_{i=1}^{n} |(y_i - y'_i)|} \tag{11}$$

4.1.4 RMSE. It is the square root of the MSE which is mean of the squared differences between prediction and actual wind power generation. It is a common method for calculating a model's error in predicting data that is quantitative. Lower RMSE values indicate a better fit. The RMSE is defined as:

$$\boldsymbol{RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y'_i)^2}} \tag{12}$$

4.1.5 MAPE. It defines accuracy as a percentage, calculated as the average of the absolute percentage errors of predictions. It provides a simple interpretation in terms of percentage errors. A lower MAPE value means better prediction accuracy. It can be computed as:

$$\boldsymbol{MAPE = \frac{\sum_{i=1}^{N} |A_i - F_i|}{N} \times 100} \tag{13}$$

Where A_i is representing actual value, F_i is the forecasted value, and N is representing number of fitted points.

4.2 Cases

This section discusses the two cases that was considered and analysed their results.

4.2.1 Case I. Case I involves the time series analysis the dataset that was prepared to enable one-day forecasting on an hourly basis utilizing various ML models, including ANN, SVM-Linear, SVM-Poly, and SVM-RBF. Initially, the dataset was transformed into an hourly format, where the power generation values were aggregated into one-hour intervals. This data restructuring allowed for a 24-hour lagged time series, effectively shifting the dataset 24 times to produce new columns that encapsulate the data from each of the previous 24 hours. These columns serve as lagged inputs, which, along with other relevant features, are fed into the ANN, SVM-Linear, SVM-Poly, and SVM-RBF models. By incorporating these lagged inputs, the models can identify and learn from the temporal patterns embedded within the data, enhancing their ability to predict the power generation for the subsequent hour more accurately.

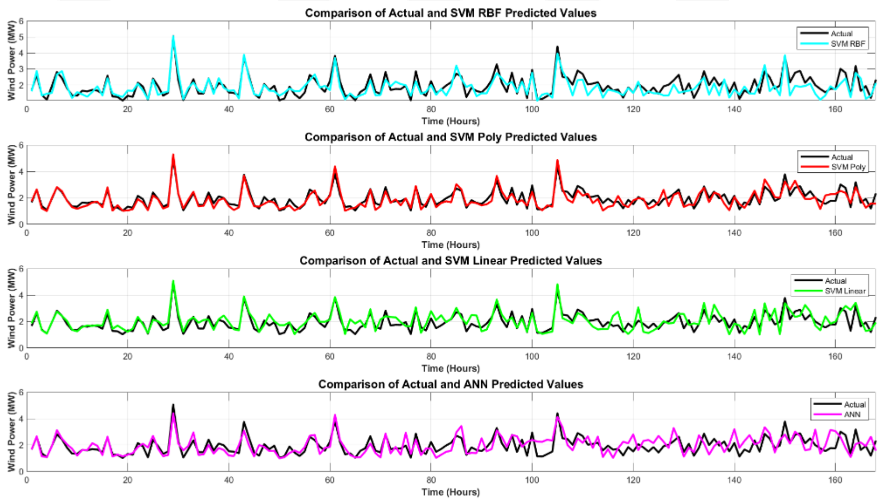

Figure 11. Models comparison in terms of wind power generation.

Error! Reference source not found. compares the actual wind power g eneration data against predictions made by three different SVM models, SVM RBF, SVM Poly, and SVM Linear and an ANN. It is evident from the visualization that the SVM Poly model exhibits the closest alignment with the actual data, suggesting a superior performance in capturing the complex, non-linear patterns inherent in wind power generation. The SVM Poly's forecasts correspond closely to the actual output over the time series, suggesting its competence in dealing with the dataset's variability and complexities. While the SVM Linear model appears to follow the data trend, it does not capture the peaks and valleys as precisely as the SVM Poly, which is expected given its inherent limitation with non-linear data. Although the SVM RBF and ANN models show some degree of correlation with the actual data, they exhibit disparities at several points, implying a less accurate representation of the data's nuances. Overall, the SVM Poly stands out with a predictive performance that suggests a robust model well-suited for the complexities of wind energy forecasting.

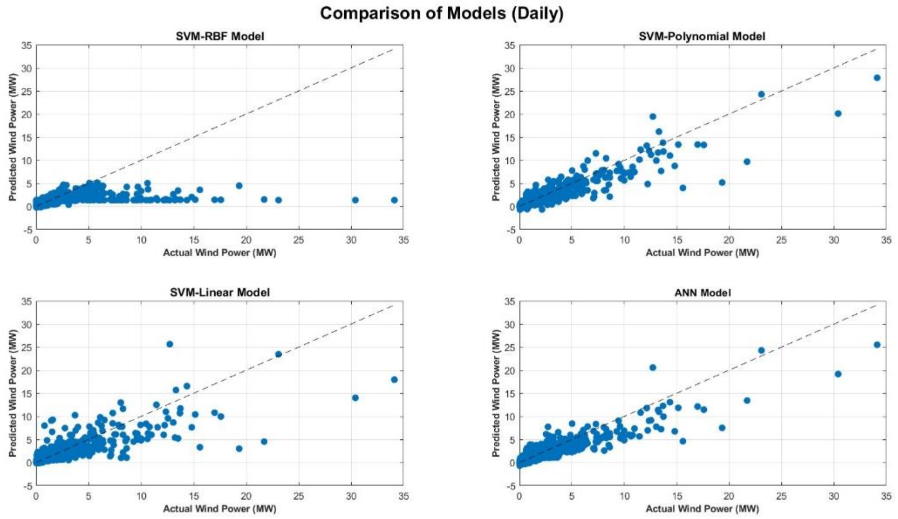

Figure 12. Comparison of models in term of next-hour forecasting.

Error! Reference source not found. shows the scatter plots of the next 24 hour f orecasting performance of four models, SVM-RBF, SVM-Poly, SVM-Linear, and ANN based on the previous day's values. Each visual compares real power output values to the numbers predicted by each model. The first subplot depicts the SVM-RBF model's scatter of points. The scattered spots do not nearly line with the diagonal, showing that there is a large difference between the expected and actual values. This shows that the SVM-RBF model may fail to capture complicated patterns in the data. The second subplot, which represents the SVM-Polynomial model, displays points that are more firmly packed around a diagonal line, especially at lower real power values. This suggests a higher prediction accuracy, particularly in the area of lower power outputs, implying that the SVM-Polynomial model captures the relationship in the data better. The predictions of the SVM-Linear model cluster around the diagonal in the third subplot, but with a constant underestimating over the entire range of values, shown by the spots dropping below the diagonal line. This model has a linear forecasting bias, which may be a problem when dealing with non-linear wind power data. The ANN model's fourth subplot indicates a good alignment to the diagonal line, with some locations deviating greatly from it. This implies that although an ANN model generally catches patterns in the data, its forecasts are not always accurate. Ultimately, the SVM-Polynomial model outperforms the others, especially in the lower range of the power outputs, where its predictions nearly match the actual values. The accuracy and bias of the other models varies, with the ANN model usually adhering to the trend but with some noteworthy inaccuracies and the SVM-Linear model demonstrating a consistent underestimate trend across all values.

4.2.2 Case II. Case II is about the data preparation process in which transforming from high-frequency (hourly) records to a daily timescale is involved. Each data point was computed as the mean of 24 hourly values, representing the average daily power generation. To capture the temporal dependencies, seven lag variables were created, each corresponding to the power output of one of the previous seven days. This approach shifts from the 24-hour lag used in Case I, aligning the model to forecast the next full day's generation rather than the next hour. These seven delayed inputs and extra feature inputs were used to train the ANN and SVM models, which included Linear, Polynomial, and RBF. The models attempted to extract deep patterns from the previous week's data in order to forecast wind energy output for the next day. This daily prediction model is especially useful for operational scheduling and grid management, as it provides a more comprehensive view of energy production.

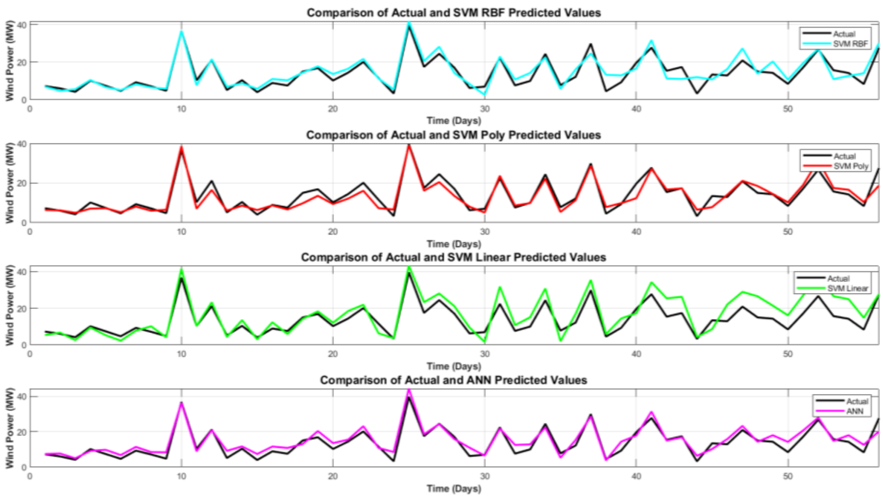

Figure 13. Comparison of models in term of daily wind power generation.

Error! Reference source not found. provides the implemented models p erformance for the daily wind power generation over a one-month period. Observing the graphical depiction, it is clear that this SVM-Polynomial model has the most accurate predictions which infers that it can perform well in daily forecasting. Because it has potential of capturing fluctuations in the generation of wind energy which implies that the SVM-Polynomial's non-linear model is suitable to the data with complex patterns. While the other models, to varied degrees, follow the broad trend, they do not stick as closely to the exact data points as the SVM-Polynomial approach does. It can be seen that SVM-Linear model has also good performance, although it has linear approach which is less effective for the modelling of complexities of the data than the polynomial kernel. The other two models ANN and SVM-RBF models shows the more significant fluctuation from the actual at various points in the graphs. This implies that these models are not capturing the non-linear behaviour of data effectively. In this wind energy forecasting case, the SVM-Polynomial model is the most accurate among others, showing the model's stability and potential for accurately

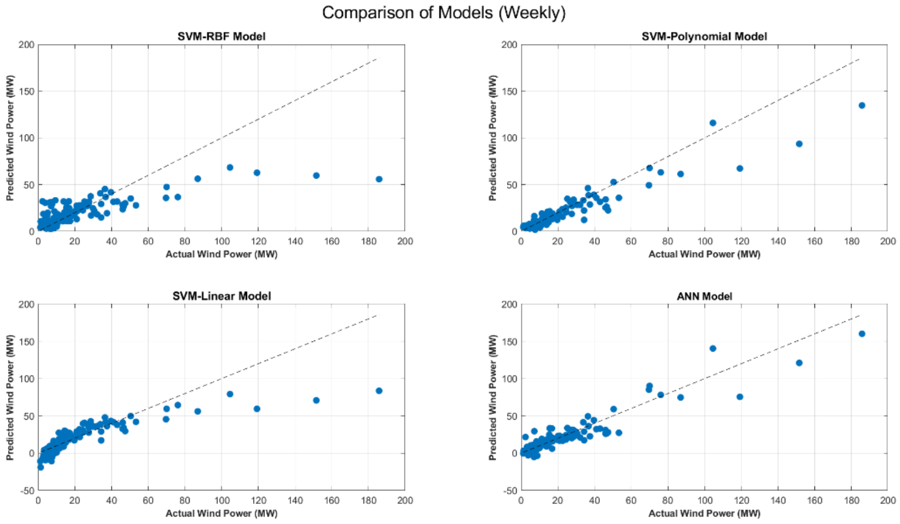

Figure 14. Models' performance in term of next-day forecasting.

predicting daily energy outputs.

Error! Reference source not found. shows the performance of implemented m odels for next-day forecasting using data from the previous week in terms of their predicted wind power values versus the actual values. The SVM-RBF model is showing the low prediction accuracy in comparison to the actual values. This implies that the model could not capture the underlying patterns effectively of the dataset for

next-day forecasting. In case of SVM-Linear model, predictions are along the actual line but not exactly.
This behaviour implies that the predictions of the model are biased in a systematic way and it has is a linear relation with actual target. But it does not sufficiently reflect the complicated trends in the data. In case of SVM-Polynomial model, predictions of the model are more closed to the actual values and correspond to the diagonal line than the other two SVM models. This well alignment implies that the SVM-Polynomial model is more effective in capturing and detecting the non-linear relation in the wind power data and provides better next-day forecasts. The fourth subplot shows the ANN model predictions. This misalignment shows that the ANN model is not suitable to learn the essential patterns of the dataset more effectively for accurate next-day predictions.

4.3 Efficiency of the Models

The efficiency of a model not only encapsulates its prediction accuracy but also how resource-intensive the process is, in particular, the time it takes to train the model. Table 6 shows the training times for different models used for daily and weekly wind power forecasting. For daily forecasting, the ANN model requires the least amount of time, indicating high computational efficiency. However, for weekly forecasting, the training time for ANN increases significantly, surpassing the SVM-Linear and approaching the training times of the more complex SVM-Poly and SVM-RBF models. The bar chart reveals that while ANN might be the most efficient for daily forecasting, its efficiency decreases with more extensive data sets, as seen in the weekly forecasting scenario. SVM-Linear, on the other hand, maintains a consistent training period, demonstrating its applicability for short model ready circumstances. SVM poly and RBF models have the more training times compared to linear model of SVM because of their potential to capture complex patterns and complicated correlations in the data.

Error! Reference source not found. provides the comparison of MAE for i mplemented models considering the everyday and weekly wind energy predictions. It can be observed that the SVM-Poly model is performing better than all other models for daily wind energy predictions. This implies that it has potential to capture daily fluctuations in the data. The ANN model is performing better that the SVM-Linear model. This implies that ANN model is more suitable for daily forecasting compared to the linear SVM approach. The SVM-RBF model provides a poor prediction capability compared to others for daily forecasting. In the consideration of weekly prediction, SVM-Poly model is again the most accurate model, showing that it has potential to identify and forecast complex, non-linear patterns. It is suitable for weekly predictions. While the ANN model is showing poor performance for weekly predictions than the SVM-Poly model. ANN model outperforms the other two models of SVM. As the other two models less suitable for capturing longer-term relationships in weekly data.

Table 6

Training Time of the Implemented Models.

Forecasting type	Training Time in Seconds			
	ANN	SVM-Poly	SVM-RBF	SVM-Linear
Daily	27.52	22.12	4.12	1.57
Weekly	3	0.61	0.42	0.32

Table 7

Models Evaluation in terms of MAE for Daily and Weekly Wind Power Forecasting.

Our Implemented Models	MAE	
	Daily	Weekly
SVM RBF	0.0076	0.0224
SVM Poly	0.0046	0.0122
SVM Linear	0.0059	0.0212
ANN	0.0052	0.0176

Error! Reference source not found. shows the models performance in terms of M SE metric for predicting wind power generation daily and weekly. It can be seen that the SVM-Poly and ANN models are outperforming the other two version of SVM models in daily predicting. The lower value of MSE for SVM-Poly and ANN shows that they have a more robust forecast accuracy for daily output. This is ultimately showing that these models can capture day to day fluctuations in wind energy production. It can also be seen that SVM-Poly and ANN are performing better for in case of weekly forecasting too with significant lower MSE value compared to the other two models. This infers that the SVM-Poly and ANN models can effectively capture non-linear trends and longer-term trends in weekly data more effectively. The higher MSE value of the SVM-RBF and SVM-Linear models shows that these models are not effective for capturing the data's weekly variability. Overall, SVM-Poly and ANN, models with non-linear capabilities resulted in more accurate forecasts for daily and weekly predictions. This indicates that these models can be used for tasks requiring complex pattern recognition. The selection among SVM poly and ANN models depends on other factors as well such as training time, computing power, and unique application needs.

Table 8

Models Performance in Terms of MSE for Daily and Weekly Wind Power Forecasting.

Our Implemented Models	MSE	
	Daily	Weekly
	1.0e-03 *	
SVM RBF	0.5995	0.0019
SVM Poly	0.1298	0.0006
SVM Linear	0.2446	0.0013
ANN	0.1278	0.0006

The RMSE for multiple ML models employed in forecasting wind power is shown in **Error! Reference source not found.**. For daily forecasting, the ANN model p erforms quite well, followed closely by the SVM-Poly model. Both models exhibit significantly lower RMSE values than the SVM-RBF and SVM-Linear models, showing a better fit for daily predictions. The SVM-Poly model outperforms the other three models in weekly forecasting, although with a slightly greater RMSE score than in daily forecasting. The ANN model fits the weekly data well as well, very similarly to the performance of the SVM-Poly model. The RMSE values for the SVM-RBF and SVM-Linear models are greater for daily and weekly forecasts, showing that they could be less effective at modeling the temporal trends in the generation of wind energy data over these time periods. Ultimately, the non-linear models, SVM-Poly and ANN, are superior at daily and weekly wind power forecasting because they handle the intricacies inherent in predicting wind energy output better.

Table 9

Comparison of Models in Terms of RMSE for Daily and Weekly Wind Power Forecasting.

Our Implemented Models	RMSE	
	Daily	Weekly
SVM RBF	0.0245	0.0440
SVM Poly	0.0114	0.0246
SVM Linear	0.0156	0.0366
ANN	0.0113	0.0243

The MAPE for all of the models is shown in **Error! Reference source not found.**, which displays the accuracy of the models in terms of percentages for daily as well as weekly wind power predictions. A lower MAPE suggests a model that predicts values that are closer to the actual values, implying more accuracy. The SVM-Poly model outperforms the SVM-RBF model for daily forecasting, while both outperform the SVM-Linear and ANN models significantly. When dealing with the unpredictable nature of wind energy production data, the much larger MAPE for SVM-Linear shows that this model may not be as useful for daily prediction tasks. In the weekly forecasting scenario, the SVM-Poly model emerges with the best accuracy, having the lowest MAPE among the models, indicating its predictive solid capability over extended periods. While not performing as well as SVM-Poly, the ANN model shows an improvement compared to its daily forecasting performance, suggesting its potential utility in applications with a less immediate forecasting requirement. Both the SVM-RBF and SVM-Linear models have higher MAPE values for weekly forecasting, with SVM-Linear having the highest error, which may reflect limitations in capturing the longer-term trends in the data. Overall, the SVM-Poly model is the most reliable for forecasting wind power on both daily and weekly bases, likely due to its ability to effectively model complex, non-linear relationships within the data.

Table 10

Comparison of Models in Terms of MAPE for Daily and Weekly Wind Power Forecasting.

Our Implemented Models	MAPE	
	Daily	Weekly
SVM RBF	13.2444	17.5080
SVM Poly	12.5365	9.9833
SVM Linear	26.5318	21.6404
ANN	20.9882	20.0856

In the short-term forecasting performance analysis with normalized values, the models exhibit varied proficiency across different metrics as shown in Table 11. The SVM-Poly model outshines the others, presenting the lowest values in MAE and RMSE, indicating its superior accuracy in capturing the nuances of wind energy forecasting. It also shows commendable results in MSE and has one of the lowest MAPE scores, confirming its consistency in prediction quality. The SVM-RBF model, while not as precise as the SVM-Poly, still maintains moderate accuracy across all metrics. It can be observed that the performance of the ANN model is comparable with SVM-Poly in terms of MSE and RMSE which implies that it has potential for modelling complicated patterns. In case of SVM-Linear, it has well performance in terms of MAE, but it lags significantly in terms of MAPE. This implies that it has the limited capability to handle the randomness aspects in wind power data. In general, the SVM-Poly model performs well and suitable for short-term wind power forecasting.

Table 11

Short-Term Forecasting Performance Analysis with Normalized Values.

Our Implemented Models	MAE	MSE 1.0e-03 *	RMSE	MAPE
SVM RBF	0.0076	0.5995	0.0245	13.2444
SVM Poly	0.0046	0.1298	0.0114	12.5365
SVM Linear	0.0059	0.2446	0.0156	26.5318
ANN	0.0052	0.1278	0.0113	20.9882

The performance evaluation for medium-term forecasting for implemented models are shown in Table 12. It can be observed that the SVM-Poly model has the lowest values of MAE and RMS. This implies that SVM polynomial model is effective and has ability to make accurate forecasts over a medium-term timeframe. It also has the lowest value of MSE compared to the ANN model, showing an effective capturing of data trend. The SVM-Poly model has the smallest MAPE value which implies that its predictions are close to real values but proportionally constant across the dataset. The other two variant of SVM show the poor performance. It can be seen that SVM-Linear model has the highest value of MAPE which infers its limitation in medium-term prediction capabilities. The ANN model has a comparable values of MSE and RMSE compared to SVM-Poly but have higher value of MAPE. Overall, the performance evaluation shows that the SVM-Poly model is performing well in medium-term forecasting. The comparable MSE and RMSE values of ANN model compared to SVM-Poly make ANN a feasible alternative.

Table 12

Medium-Term Forecasting Performance Analysis with Normalized Values.

Our Implemented Models	MAE	MSE	RMSE	MAPE
SVM RBF	0.0224	0.0019	0.0440	17.5080
SVM Poly	0.0122	0.0006	0.0246	9.9833
SVM Linear	0.0212	0.0013	0.0366	21.6404
ANN	0.0176	0.0006	0.0243	20.0856

Chapter 5

Discussions and Conclusions

The wind power forecasting accuracy is critical in renewable energy for incorporating wind energy into conventional power networks. The comparison study on wind energy prediction was thorough. Among the studied models, SVM-Poly consistently beats others in daily and weekly forecasting scenarios, according to our data. Examining multiple error metrics revealed that the SVM-Poly model had the lowest error rates, indicating a strong appropriateness for complicated recognition of patterns in wind speed as well as power output data. Across several error criteria, each model demonstrated distinct strengths and drawbacks. The capacity of the SVM-Poly to catch non-linear trends was obvious, making it preferable for medium-term forecasting.

SVM-RBF and SVM-Linear, on the other hand, shown poor performance in capturing the unpredictability of wind power generation despite their simplicity and lower processing demand. The model's performance was heavily influenced by the input features. The fluctuations of wind power potential were captured by measuring wind speed and direction. SVM-Poly and ANN models performed well and shown their capacity to handle such data complexity. However, it is important to note this analysis is performed using specific dataset so the performance of these models may vary with other considerations and under different parameter settings. Improved forecasting accuracy has a direct impact on grid management, allowing for greater wind power integration and more reliable power planning. The effective forecasting will facilitate the possible economic savings and improved grid stability which are important in widespread adoption of energy from renewable sources. Different applications have different requirements so the application's specific model development should be considered for wind power forecasting. The balance approach with technological capabilities as well as practical application should be prioritize so that energy sources that are renewable can be efficiently used and smoothly incorporated into our energy systems.

Integration of the diversified range of meteorological and atmospheric data will be advantageous in future of wind power forecasting. This integration with a variety of geographical areas and time spans as well as additional atmospheric characteristics, will improve the flexibility of predictive models. In the future, using hybrid and ensemble models can provide enhance the predictive capabilities of diverse approaches, such as SVMs and ANNs, to capture a broad range of patterns in data. As models become more complicated, the computational expenses can become prohibitively expensive. More efficient algorithms, parallel computing, and GPU acceleration can significantly reduce these costs, making updated models easier to use for real-time forecasting. Deep learning algorithms created exclusively for time series data, such as RNNs and LSTM networks, could considerably improve prediction accuracy by identifying temporal relationships in the speed and direction of the wind patterns. Dedicated feature engineering study, discovering the most predictive traits and altering them as needed, could deliver significant benefits. Selection of features algorithms can automate the selection of the most relevant characteristics, which reduces the complexity of models and training time. As climatic patterns change, it is critical to analyse how these changes can impact wind patterns and, thus, wind power generation. Models should be capable of accommodating long-term changes in the distribution of data caused by climate change. Finally, including measurement of uncertainty into forecasts for models can provide essential information regarding prediction confidence, which is especially useful for managing risks in energy marketplaces and grid stability assessments.

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