Enhancing Wind Energy Forecasting Efficiency through Dense and Dropout Networks (DDN): Leveraging Grid Search Optimization

By:

Talal Alazemi

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Department of Electronic and Computer Engineering,

Collage of Engineering, Design and Physical Sciences

Brunel University London

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Abstract

This research investigates wind energy forecasting using a Deep Dense Network (DDN) method enhanced by Grid Search Optimization. It begins with an introduction to wind energy mechanics and machine learning principles, setting the stage for the study's main problem. Further, a comprehensive literature review explores recent machine learning trends for Renewable Energy Sources (RES) output estimation, including deep Neural Networks (NN), Support Vector Regression (SVR), Support Vector Machines (SVM), and other forecasting models, discussing their advantages and disadvantages.

The proposed methodology focuses on the Deep Dense Network (DDN) model, detailing its algorithm. The dataset incorporates several variables, such as wind speed, wind direction, temperature, and air pressure and was scaled. A DDN model with eight dense layers of 512, 256, 128, 64, 32, 16, and 8 neurons, each followed by dropout layers (rate 0.4) and using ReLU activation, was designed. The final output layer, with a single neuron, predicts system power. The model was compiled with the Adam optimizer (learning rate 0.1), minimizing MSE and MAE. Early stopping (patience 50 epochs) was employed to prevent overfitting. Grid Search Optimization was applied to fine-tune parameters such as learning rate, dropout rate, batch size, and epochs, improving prediction results

The evaluation employs two key metrics: Mean Squared Error (MSE) and Mean Absolute Error (MAE). Together, these metrics provide a comprehensive evaluation of the DDN model's performance by capturing both the average error magnitude (MAE) and emphasizing larger errors (MSE), offering a balanced assessment of prediction accuracy and error distribution. The results demonstrate the model’s capability to converge, indicating effective learning from the data. The application of MSE and MAE metrics substantiates the model's accuracy, with significant reductions in these values reinforcing the proposed approach's validity. Specifically, the MSE decreased from 0.0785 before Grid Search Optimization to 0.0047 after optimization, achieving a 94.013% improvement. Similarly, the MAE reduced from 0.2376 to 0.0548, reflecting a 76.8474% improvement. These substantial enhancements validate the effectiveness of the proposed model. Given the relatively nascent state of renewable energy and deep learning fields, this study offers valuable insights and proposes several directions for future research, establishing a solid foundation for further advancements in this area.

List of Publications

1. 'TSO/DSO Coordination for RES Integration: A Systematic Literature Review'. *Energies*, 15 (19). pp. 7312 – 7312. (2022)

2. 'Wind Power Generation Forecast Using Artificial Intelligence Techniques'.*58th International Universities Power Engineering Conference (UPEC).* Dublin, Ireland. 30 - 1 September. IEEE. pp. 1 - 5. (2023)

3. 'Renewable energy sources integration via machine learning modelling: A systematic literature review'. *Heliyon*, 10 (4). pp. 1 - 30. ISSN: 2405-8440 (2024)

4. 'Enhancing Wind Energy Forecasting Efficiency through Dense and Dropout Networks (DDN): Leveraging Grid Search Optimization'. Submitted to Energy Report Journal (Under review)

Table of Contents

List of Figures

List of Tables

List of Abbreviations

Abbreviation	Definition
ANN	Artificial Neural Network
BC	Box-Cox Transformation
CEEMD	Complete Ensemble Empirical Mode Decomposition
CNN	Convolution Neural Network
CORR	Correlation Matrix Analysis
DDN	Dense and Dropout Network
DM	Diebold-Mariano
DTs	Decision trees
ELM	Extreme Learning Machine
FAP	Future Accurate Prediction
GB	Gradient Boosting
GHGs	Greenhouse Gases
GRU	Gated Recurrent Units
GSR	Global Solar Radiation
IMFO	Improved Moth-Flame Optimization
IMFs	Intrinsic Mode Functions
k-NN	k-Nearest Neighbors
LR	Logistic Regression
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MLP	Multilayer Perceptron
MPPT	Maximum Power Point Tracking
MSE	Mean Square Error
PCA	Principal Component Analysis
PSO	Particle swarm optimization
REG	Renewable Energy Generation
REPP	Renewable Energy Performance Platform
RES	Renewable Energy Source
RF	Random Forest
RMSE	Root-Mean-Square Error
RNN	Recurrent Neural Network
SLFNs	Single-Hidden Layer Feedforward Neural Networks
SLR	Systematic Literature Review
SVM	Support Vector Machine
SVR	Support Vector Regression
UC	Unit Commitment
WPF	Wind Power Forecasting
WT	Wavelet Transform

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CHAPTER 1: Introduction

In the introduction chapter, the pressing challenges facing the planet are delved into, characterized by finite resources and the environmental consequences of fossil fuel consumption. Earth Overshoot Day serves as a stark reminder of the imbalance between our resource consumption rate and nature's renewal capacity. The solution to these challenges lies in renewable energy sources, particularly wind energy. Wind energy has witnessed remarkable growth and plays a crucial role in addressing sustainability concerns. However, the efficient utilization of wind energy is contingent on accurate forecasting. The significance of this research is underscored by the increasing penetration of wind energy in power systems, the broader optimization of Deep Learning models, and the potential for cost reduction and improved power output in the wind power industry. Furthermore, the research aligns with the global transition towards clean and renewable energy sources, contributing to the overarching goal of sustainability. This introductory chapter provides the foundation for the subsequent chapters, offering readers a comprehensive understanding of the study's context and objectives.

This study serves as a comprehensive review of the results and discussions derived from the development and implementation of the DDN model for enhancing wind energy forecasting efficiency. Building upon the backdrop of the global energy landscape's evolution and the growing significance of wind power as a renewable energy source, this study presents a detailed exploration of the DDN model's performance and its implications for the renewable energy sector. The DDN model represents a novel deep learning-based approach aimed at addressing the complexities and uncertainties inherent in wind energy forecasting. By leveraging dense layers for intricate data pattern recognition and dropout regularization to mitigate overfitting, the model demonstrates promising potential for improving the accuracy and reliability of energy production predictions from wind turbines. Furthermore, the integration of grid search optimization techniques enhances the model's efficiency by systematically identifying optimal hyperparameters. Through rigorous evaluation using real-world data from the "Texas Turbine" dataset, this study assesses the DDN model's performance in terms of Mean Squared Error (MSE) and Mean Absolute Error (MAE). The results reveal significant improvements in accuracy following grid search optimization, demonstrating the model's effectiveness in predicting energy production from wind turbines. Moreover, this chapter offers a comprehensive discussion of the findings, comparing the performance of the DDN model with existing forecasting techniques and identifying areas for further improvement. It delves into the implications of the model's accuracy for renewable energy management and distribution, highlighting its potential to contribute to a more sustainable energy future.

1.1 Introduction

The planet's resources are finite, and unfortunately, the rate of consumption outpaces the earth's natural capacity to replenish them. To illustrate this concern, It can reflect on August 13, 2015, a significant date known as Earth Overshoot Day [1], [2]. On this day, the global resource consumption for the year exceeded the earth's ability to renew these resources [3]. In simpler terms, to find ourselves in the unsettling position of borrowing resources from the planet's future, a practice that continues to escalate with each passing year [4]. Compounding this challenge is the critical role played by fossil fuels, including coal, petroleum, and natural gas, in the history [5]. These fossil fuels have served as the primary energy source, facilitating industrialization, and powering modern transportation systems [6].

However, the unsustainable exploitation of natural resources carries profound consequences, ultimately leading to ecological imbalances [7], [8]. More worrisome is the global combustion of these fossil fuels, which has given rise to a pressing environmental crisis. The excessive emissions of GHGs , most notably carbon dioxide, stemming from the combustion of fossil fuels, pose a severe threat to the environment [4], [8]. These emissions have contributed to a range of critical issues, including the abnormal rise in carbon dioxide levels, global warming, and the detrimental effects of acid rain. A poignant example of the detrimental consequences of fossil fuel use can be observed in the severe air pollution experienced in northern China in recent years [6], [9]. This underscores the urgent need to address the negative environmental impact resulting from the reliance on these finite resources. Considering these interconnected challenges, it becomes evident that the transition to cleaner and more sustainable energy sources is not merely a choice but an imperative [10]. The urgency is further accentuated by the accelerating pace of unsustainable resource consumption [9], [11]. To contemplate a sustainable future, responsible resource management and the adoption of sustainable energy practices emerge as paramount priorities [10], [11]."

Renewable energy (RE) sources, such as solar, wind, and biomass energy, stand out as the most effective approach to addressing these pressing challenges. RE can be harnessed from a wide array of sources, including hydropower, biomass, geothermal, wind, and solar power

[12]. The wind energy sector has experienced remarkable growth, driven by a combination of technological advancements and innovative business strategies [13]. In the year 2020, global wind power capacity surged to an astounding 93 GW, marking an impressive 52.96% increase compared to the preceding year [14], [15]. This notable surge underscores the pivotal role of the wind energy sector in addressing both the growing energy needs and pressing sustainability concerns. But, against the backdrop of this promising development lies a sobering reality [13]–[15].

Wind energy generated by wind turbines represents a sustainable and environmentally friendly energy solution [6], [16]. Thanks to ongoing technological advancements and innovative business models, the wind power industry is experiencing substantial growth, leading to a significant increase in its installed capacity [11], [17]. As the socioeconomic landscape undergoes rapid expansion, the demand for energy has surged to meet the everyday needs and activities of the communities [2], [17]. Wind power is essentially the process of converting the kinetic energy found in moving air into electricity. However, this conversion is influenced by various factors including wind speed, wind direction, air pressure, and temperature [2], [18]. Even a minor change of just 1 meter per second in wind speed within a wind farm that generates energy can result in significant fluctuations in power output [18], [19]. This occurs because the relationship between wind speed and the power generated is not a straightforward one [19], [20]. To illustrate, a survey conducted across 19 companies revealed that achieving a mere 1% improvement in reducing prediction errors could potentially save up to 10,000 megawatts of electricity [21]. This highlights the substantial cost-saving potential of an efficient Renewable Energy Performance Platform (REPP) model, with estimated annual savings of approximately $1.6 million [22]. Recent research efforts have been notably focused on developing and implementing techniques for the prediction of wind energy generation [23].

In the current body of research, these methods are typically categorized into four primary groups: statistical, physical, intelligent, and hybrid techniques[7], [8], [23]. Statistical approaches entail the prediction of wind energy by utilizing probability distributions and random processes [23], [24]. On the other hand, physical methods rely on meteorological data, including factors such as topography, atmospheric pressure, and temperature, to make their predictions [24]. Table 1.1 is the overview of all techniques with its strength and limitation.

Table 1.1: Techniques of wind energy prediction

Categories	Description	How it works	Strengths	Limitations
Statistical Methods	Statistical methods for predicting wind energy rely on historical data and mathematical models. They analyze patterns and trends in past wind energy generation to make future forecasts. How They Work: These methods use statistical tools like probability distributions and random processes to estimate future wind energy output. They consider factors such as the time of day, season, and historical wind patterns to make predictions	These methods use statistical tools like probability distributions and random processes to estimate future wind energy output. They consider factors such as the time of day, season, and historical wind patterns to make predictions	Statistical approaches are useful for capturing long-term trends and seasonal variations in wind energy production. They are relatively simple to implement and can provide valuable insights into the probabilistic nature of wind energy	They may struggle to capture short-term fluctuations and sudden changes in wind patterns.
Physical Methods	Physical methods for wind energy prediction focus on the direct influence of meteorological variables on wind generation. They incorporate data related to topography, atmospheric pressure, temperature, and other environmental factors.	These methods use physics-based models to simulate the behavior of the atmosphere and wind patterns. By considering the physical interactions of air masses, terrain, and atmospheric conditions, they aim to make precise wind energy forecasts.	Physical methods excel in capturing short-term variations and the impact of specific weather events on wind energy production. They provide detailed insights into the underlying mechanisms of wind generation.	They can be computationally intensive and require accurate meteorological data, which may not always be readily available.
Intelligent Methods	Intelligent methods involve the use of artificial intelligence (AI) and machine learning techniques to predict wind energy. These methods can learn from historical	Machine learning algorithms, such as neural networks and decision trees, are trained on historical wind energy data. They can identify complex patterns and	Intelligent methods can handle large and complex datasets, making them suitable for fine-grained wind energy forecasting. They can adapt to	They may require substantial computational resources and a large amount of training data to

	data and adapt their predictions over time	relationships in the data to make predictions.	changing conditions and improve accuracy with more data.	perform optimally
Hybrid techniques	Hybrid methods combine elements of the other three categories—statistical, physical, and intelligent approaches. They leverage the strengths of each to improve prediction accuracy.	Hybrid methods integrate statistical models, physical principles, and machine learning algorithms. This combination allows for a more comprehensive and robust approach to wind energy prediction.	Hybrid methods aim to overcome the limitations of individual approaches by combining their strengths. They can provide accurate and reliable forecasts for both short-term and long-term wind energy generation.	Developing and implementing hybrid methods can be complex, requiring expertise in multiple domains.

As, the rate of resource consumption exceeds the earth's natural renewal capacity, as demonstrated by Earth Overshoot Day. The use of fossil fuels has resulted in environmental problems, such as the emission of GHGs and air pollution [1] [25]. To address these challenges, renewable energy sources like wind energy are essential. Wind power, generated by wind turbines, is sustainable but influenced by various factors, impacting its efficiency. Efficient wind energy prediction methods, including statistical, physical, and approaches, are critical for optimizing energy production and reducing costs [2], [8], [16], [21], [24], [26].

1.2 Working procedure of wind energy generation

Wind energy generation is a multi-step process that harnesses the kinetic energy of moving air to produce electricity [27]. It begins with the strategic placement of wind turbines in locations known for consistent and strong wind patterns [28]. These turbines are equipped with rotor blades that capture the wind's kinetic energy, causing them to rotate. As the blades turn, they transfer this mechanical energy to a generator located within the turbine's nacelle, where it is transformed into electricity [29], [30] The electricity generated is typically in the form of Alternating Current (AC), the standard for most electrical applications [31]. To optimize power output and ensure safe operation, wind turbines are equipped with control systems that adjust the pitch angle of the rotor blades and the orientation of the nacelle [31], [32]. This adaptation enables the turbine to operate efficiently within its designed range of wind speeds [33], [34]. The electricity is then transmitted within the turbine's tower through cables to an on-site substation, where it passes through a step-up transformer to increase its voltage for long-distance transmission [35][36].

The high-voltage electricity is transferred to the electrical grid, often through a dedicated connection point for wind farms [37]. From the grid, the electricity is distributed to homes, businesses, and industries, serving a variety of purposes, including lighting, heating, and running appliances [28], [38]. Wind energy generation is integrated with other energy sources on the grid to ensure grid stability and grid operators carefully balance the supply and demand of electricity to maintain a reliable power supply. Where, Figure 1 illustrates the renewable energy system, highlighting renewable energy sources like solar panels and wind turbines generate electricity, which can be used immediately or stored in batteries for later use. A generator acts as a backup power source, providing electricity when renewable sources and the grid are unavailable. The smart meter plays a crucial role by recording real-time energy consumption and generation, allowing for efficient energy management and communication with the utility company for billing and supply monitoring. both schedulable and non-schedulable appliances.

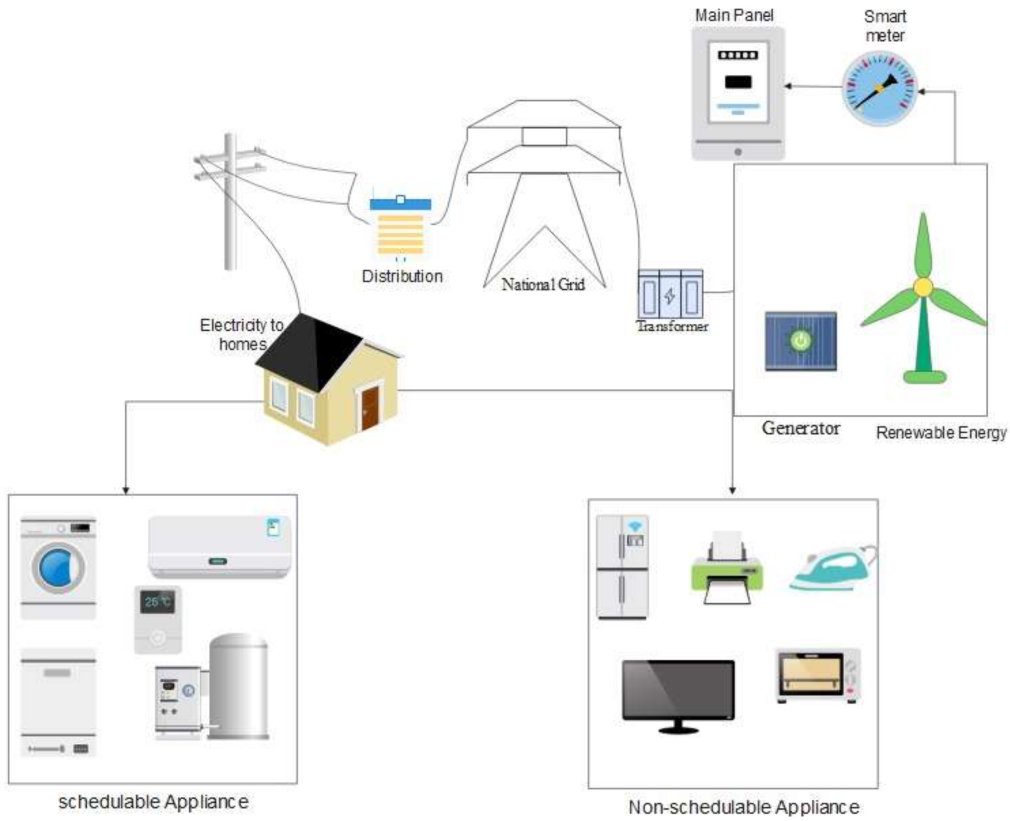

Figure 1.1: Wind energy and electricity to home

Monitoring and maintenance play a critical role in the wind energy generation process, ensuring the continued efficiency and reliability of wind turbines [27]. Routine maintenance addresses wear and tear and helps prevent equipment failures [28]. Additionally, some wind energy systems may incorporate energy storage solutions, such as batteries, to store excess electricity generated during periods of high wind for use during low-wind periods. Wind energy generation is a sustainable and environmentally friendly means of producing electricity, contributing to a cleaner and more sustainable energy future. Timely wind energy forecasting is critical due to the nonlinear relationship between wind speed and power generation—however, the complexity and uncertainty of natural wind factors present challenges, necessitating effective forecasting methods [29].

1.3 Machine Learning

Machine learning is a branch of computer science that focuses on enhancing a program's performance through learning from experience [25]. In machine learning, rather than explicitly instructing the machine on how to solve a problem, it is provided with historical data as input, and it learns to create a model that can address similar problems in the future.

Machine learning draws knowledge from diverse fields like artificial intelligence, statistics, and neuroscience. Nowadays, applications of machine learning are encountered in daily life, such as speech recognition and personalized online ads. Notable examples of its capabilities include the computer program AlphaGo, which defeated the world Go champion [2], [31]. The process of machine learning typically involves several steps. Initially, historical data is collected for training purposes. Then, an abstract target function is defined to describe the relationship between input data and the desired output. Subsequently, a machine learning model is chosen to approximate this target function. Finally, an appropriate algorithm is applied to construct the model using the training data. [17] [32]. Figure 1.2 illustrates the process of wind prediction using machine learning models. It starts with the historical data of wind power, which provides the foundational information needed for analysis. This data undergoes processing to clean, normalize, and transform it into a suitable format for the machine learning engine. The machine learning engine then uses this processed data to train the model, learning patterns and relationships within the data. Finally, the trained model generates future wind power value predictions, offering insights into expected wind power generation.

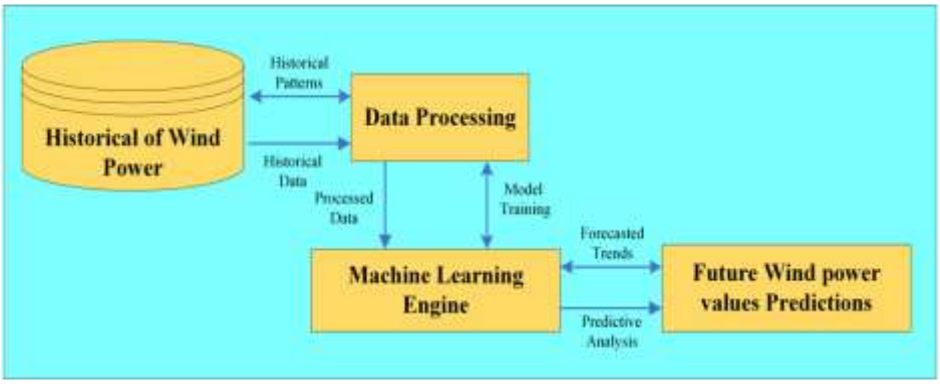

Figure 1.2 Machine learning model and wind prediction

In the context of wind power prediction, the target function usually maps weather data to future wind power output. The specific machine-learning models relevant to this application will be discussed in the following section.

1.4 Machine Learning Models

In the realm of machine learning, simpler models like Decision Trees (DTs) and k-Nearest Neighbours (k-NN) have proven to be effective in various applications. A decision tree, as its name implies, is a tree-structured model that is constructed through training examples [7],[13]. At each node of the tree, a decision is made based on one of the input attributes, and by making a sequence of such decisions, the tree leads to a leaf node, which represents the output of the target function. In contrast, the k-NN method, also named descriptively, works by determining the result through the average of k-training examples that are closest to the test sample. Typically, Euclidean distance is used to measure proximity, although more general distance definitions can be employed. When it comes to wind power prediction, two commonly employed machine learning models are the ANN and the Support Vector Machine (SVM). An ANN comprises an input layer, hidden layers, and an output layer, each composed of multiple neurons. These neurons possess the ability to learn the relationships between input and output. Input data flows through the hidden layers to produce predictions in the output layer. In practical applications, various ANN variants are used, including the Multilayer Perceptron (MLP) and recurrent ANN. In contrast, SVM is a relatively recent algorithm in the field of machine learning, employing a kernel-based approach [5], [9], [28]. The underlying mechanism of SVM is intricate, but in simplified terms, it seeks to find a hyperplane with maximal margins between two sets of training examples. This hyperplane is subsequently used for making predictions [39]. The AI based Wind Power Forecasting (WPF) framework is given in Figure 1.3

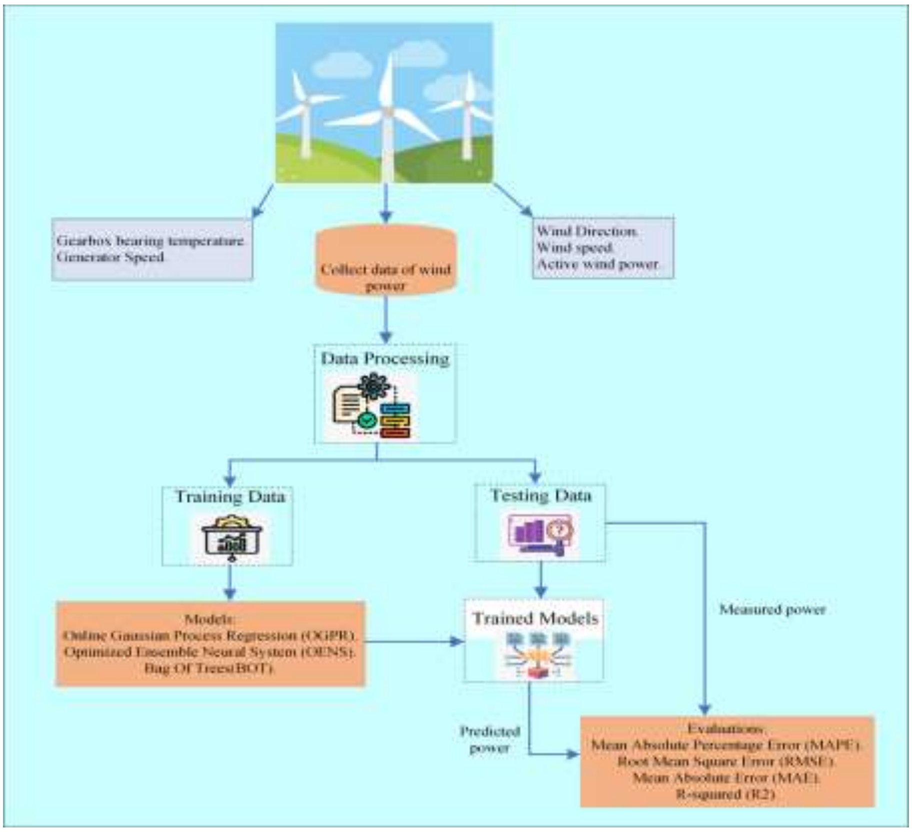

Figure 1.3 Machine learning-based WPF framework

Where, data is collected from wind machines such as temperature, wind direction, wind speed, and active wind power. This data is then processed and divided into training, testing, and validation sections. The training portion is used to train the model, while the test portion is used to evaluate the model performance. Model performance is assessed using metrics including Mean Absolute Percentage Error (MAPE), RMSE, R-squared (R^2), and MAE, and the Numerous other machine learning models, such as fuzzy systems, are also utilized for wind power prediction. Additionally, hybrid approaches that combine various machine learning techniques have been developed to further improve prediction accuracy.

1.5 Deep learning

Deep learning encompasses techniques designed to efficiently train deep neural networks, which distinguish themselves from regular Artificial Neural Networks (ANNs) by having multiple hidden layers. These additional layers increase the complexity of the model, resulting in a higher capacity for learning [1][25][28]. The enhanced learning capacity of deep neural networks allows them to grasp more abstract concepts as information passes through successive layers of interconnected neurons. One member of the deep learning family is the Convolutional Neural Network (CNN), known for its ability to excel in tasks involving spatial relations, particularly image recognition. Another valuable model for deep learning is the Recurrent Neural Network (RNN), which is adept at temporal predictions due to its capability to store previous states of neurons [21], [28].

However, the increased complexity of deep neural networks introduces a common issue known as overfitting. Overfitting occurs during the training phase when a model becomes excessively tailored to the training data, losing its ability to generalize to new, unseen data. In such cases, the model essentially memorizes the training data instead of learning from it. To address overfitting in deep learning, various techniques have been developed, including dataset expansion and the application of dropout methods [40].**Error! Reference source not found.** divided the whole process into several sections . First the required dataset has uploaded in google Colab. Data preprocessing section is used to perform the preprocessing steps on data to ensure that the data is clean, well-formatted, and suitable for analysis or model training. Further, the dataset is divided into three parts: training, validation, and test sets. During the training phase, the model learns from the training set by identifying patterns and adjusting its parameters to minimize prediction errors. The validation phase involves periodically evaluating the model on the validation set to tune hyperparameters and prevent overfitting. Finally, the testing phase assesses the model's performance on the unseen test set, providing an unbiased measure of its ability to generalize.

Performance metrics such as Means Square Error (MSE) and MAE are used to evaluate the model's success. Finally, the model is tested to generate the predicted output. This structured approach helps in developing a robust and reliable machine learning model.

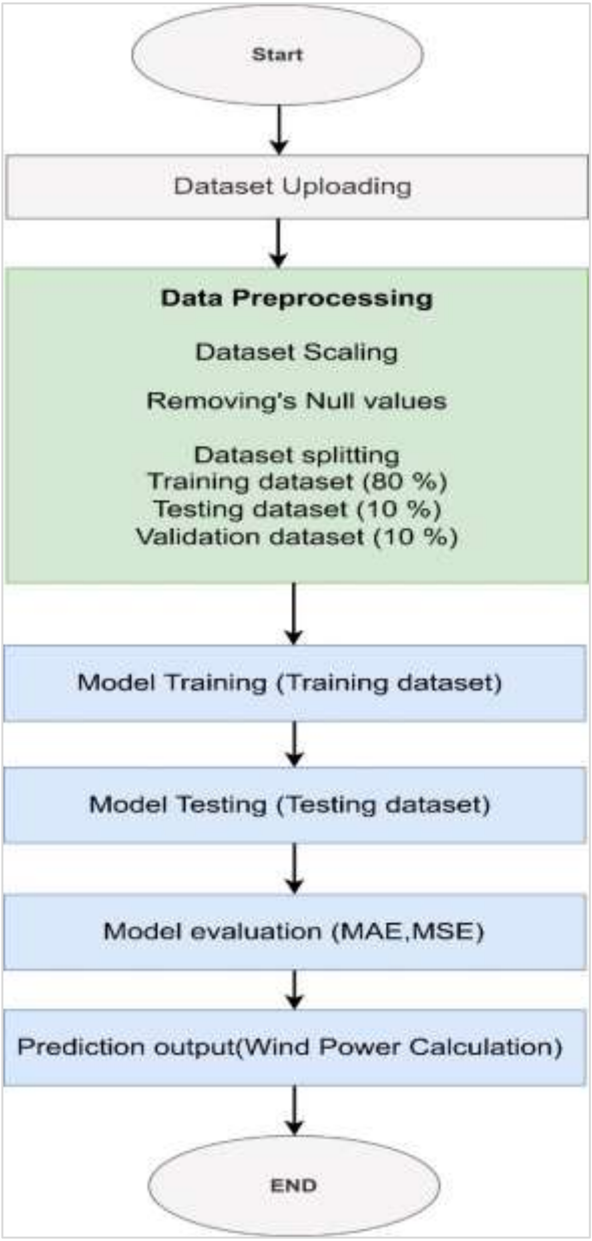

Figure 1.4 Wind prediction process

The motivation for this study stems from two key considerations. Firstly, in the domain of machine learning methods for wind power prediction, there exists a gap that calls for a comprehensive empirical investigation [3], [25], [40]. The literature review, detailed in Chapter 2, underscores the need for such research. Secondly, deep learning, being a relatively new subfield of machine learning, has demonstrated significant prowess in various problem-solving contexts. Given the limited prior work on deep learning in wind power prediction, the study is driven by a strong interest in assessing its performance in this specific domain [40].

1.6 Problem Statement

The process of generating electricity from wind power is complex, as it relies on several variables, including wind speed, direction, air pressure, and temperature [41]. Small changes in wind speed within a wind farm can lead to significant fluctuations in power output, primarily because the relationship between wind speed and power generation is not linear [42]. For instance, improving prediction accuracy by just 1% could potentially save an impressive 10,000 megawatts of electricity, translating to substantial cost savings, approximately $1.6 million annually [43], [44]. The increasing adoption of wind power in power systems, it becomes crucial to accurately predict wind power generation due to its growing impact. At lower wind penetration rates, variations in wind power supply can be accommodated, but as wind power's share in the energy mix rises, precise wind power prediction is essential [6], [45]. Accurate predictions aid in avoiding system imbalances and contribute to improved stability and efficiency. The wind power prediction process typically involves forecasting wind speed, which is then used to estimate the power output of wind farms [46]. These predictions have different time scales, with short-term predictions being particularly relevant for power dispatch planning. Wind power prediction methods can be classified into physical, statistical, and hybrid approaches, each with its own set of challenges and advantages [17], [45] The problem lies in developing effective and efficient wind power prediction models, especially for short-term forecasts, to support power systems' integration of wind energy [14], [15]. Current research is focused on tackling the challenge of accurately forecasting wind energy generation, a critical task for enhancing power output and reducing expenses in the wind power industry using deep learning.

1.7 Research Questions

RQ1: How to propose a deep learning model, that can accurately predict wind energy production forecasting using deep learning?

RQ2: How to propose a deep-learning algorithm that tunes the hyperparameter to optimize the proposed deep-learning model?

RQ3: What role can deep learn play in enhancing the accuracy of wind energy generation forecasts, and how can it contribute to improved power output and cost reduction in the wind power industry?

1.8 Research Aim

The primary aim of this research is the development of a Deep Dense Network (DDN) model designed for predicting energy production from wind turbines. To achieve this, the research meticulously crafts the architecture of the DDN model, making it essential for accurate predictions. Furthermore, the study focuses on hyperparameter tuning, seeking to optimize the model's performance by carefully selecting key hyperparameters like learning rate, dropout rate, batch size, and training epochs. The overarching objective is the reduction of prediction errors, as evaluated through the Mean Squared Error (MSE) and MAE metrics. By successfully reducing these errors, the research aims to enhance the accuracy of the model's predictions.

To make the model efficient and improve its generalization to new data, several techniques are incorporated, including dropout regularization, the use of the Adam optimizer with dynamic learning rate adaptation, and early stopping to halt training when substantial improvement ceases. The grid search algorithm is employed for systematic hyperparameter tuning, systematically testing various hyperparameter combinations to find the optimal set. The research recognizes the real-world applicability of the optimized DDN model, particularly in forecasting energy production from wind turbines. Accurate predictions in this context are instrumental in advancing efficient energy management and distribution, aligning with sustainable energy practices in the renewable energy sector. The study acknowledges that further research and data exploration could lead to even better results, indicating an ongoing commitment to refining the model and assessing its performance continuously. In conclusion, this research aims to create a valuable tool for predicting energy production from wind turbines, emphasizing accuracy, efficiency, and real-world applications.

1.9 Research Objective

- To develop a deep learning model for wind energy production forecasting.
- To optimize the deep learning model through the tuning of hyperparameters.
- To investigate the role of deep learning in improving the accuracy of wind energy generation forecasts.

- To assess how deep learning can contribute to enhanced power output and reduced expenses in the wind power industry.

1.10 Research Scope

The research scope is cantered on the development and optimization of deep learning models for wind energy forecasting, with a specific emphasis on short-term predictions relevant to power dispatch planning. Within this defined scope, the study seeks to explore the practical applications of advanced deep learning techniques in addressing the pressing challenges outlined in the problem statement. The time horizon of short-term predictions is of paramount importance, considering its direct relevance to real-time decision-making by grid operators. These predictions, typically spanning hours or days, play a crucial role in balancing electricity supply and demand, a fundamental aspect of the energy industry. Moreover, the research aims to optimize the deep learning models, fine-tuning them for enhanced accuracy in wind energy predictions. This optimization may involve adjustments in hyperparameters, model architecture, and data preprocessing techniques. Notably, the research is underpinned by a commitment to practical applicability, with the developed models and techniques intended to have tangible benefits in the wind power sector. The ultimate goal is to improve the efficiency of wind energy generation by contributing to increased power output and reduced operational costs, thereby advancing the broader goals of sustainability and renewable energy utilization. However, it is essential to acknowledge the limitations of this scope, such as the exclusion of very long-term wind energy predictions and detailed engineering aspects of wind turbines, which are beyond the study's defined boundaries.

1.11 Significant

1.11.1 Rising Wind Energy Penetration

As the global transition to renewable energy sources gains momentum, wind energy has emerged as a prominent player in power systems. This transition is driven by environmental concerns, the finite nature of fossil fuels, and the need for sustainable energy solutions. Wind energy, with its clean and renewable attributes, has witnessed a significant increase in penetration within power systems worldwide. However, as wind energy's share in the energy mix continues to grow, it introduces challenges related to grid stability and energy supply-demand balance. These challenges are particularly critical in the context of managing a power system. The research recognizes the pressing need to forecast wind energy production accurately to ensure the stability and efficiency of power systems. As wind energy becomes an increasingly significant contributor to electricity generation, the ability to predict its output with precision is vital for grid operators. Accurate predictions allow for better planning, real-time adjustments, and efficient utilization of wind power resources.

1.11.2 Optimizing Deep Learning Models

Beyond simply developing deep learning models for wind energy forecasting, this research sets out to optimize these models. The optimization process encompasses tuning essential hyperparameters such as learning rates, dropout rates, batch sizes, and the number of training epochs. By focusing on this aspect, the research contributes to the broader field of deep learning. The insights gained from fine-tuning deep learning models can extend to various applications beyond wind energy forecasting. Understanding how to tailor deep learning models for specific tasks is significant, as it can improve their overall performance and efficiency. The research's emphasis on optimization underscores the value of fine-tuning models to maximize their predictive capabilities. It also showcases the adaptability of deep learning techniques to address specific challenges in a variety of domains.

1.11.3 Cost Reduction and Improved Power Output

The financial implications of accurate wind energy predictions are substantial. The research underscores the potential for significant cost savings within the wind power industry by improving the accuracy of wind energy forecasts. Prediction enhancement in prediction accuracy can translate into noteworthy savings in electricity production costs. For example, the research highlights that a mere 1% improvement in prediction accuracy could result in annual savings of approximately $1.6 million. These cost reductions directly impact the economic viability of wind energy projects and enhance their competitiveness in the energy market. Lower production costs can lead to more affordable energy for consumers and strengthen the business case for further wind energy investments.

1.11.4 Clean Energy Transition

The transition to clean and renewable energy sources is a global imperative in the fight against climate change and the reduction of greenhouse gas emissions. Wind energy represents a key component of this clean energy transition. By advancing the accuracy of wind energy forecasts, this research aligns with broader efforts to embrace sustainable and environmentally friendly energy sources. Reliable wind energy predictions play a pivotal role in the integration and management of wind power resources. They ensure that wind energy is harnessed efficiently, reducing the reliance on fossil fuels and lowering carbon emissions. In essence, this research contributes to the overarching goal of mitigating climate change and promoting a sustainable energy future.

1.12 Methodology of the DDN model

During the development of the DDN (Dense and Dropout Neural Network) model, Python 3, a highly versatile programming language for data science and machine learning tasks, was utilized. To expedite model training, Google Colab was chosen, which harnessed the power of a GPU T4, significantly reducing computation time. For streamlined data access, the dataset was uploaded to Google Drive, providing a convenient and secure repository. By seamlessly integrating Google Drive with Google Colab's GPU environment, efficient data handling was ensured.

Firstly, the training and test data were scaled using MinMaxScaler from sklearn. This involved scaling the training data, excluding the timestamp, to facilitate effective training. The scaled data was then split into input features (X_train) and the target variable (y_train), representing system power generated. Similarly, the test data was scaled based on the parameters of the training data and then split into X_test (features) and y_test (target variable). Next, an ANN model with a Dense and Dropout Layers architecture was designed to capture complex relationships in the data. The model consists of eight dense layers with increasing complexity and dropout layers (with a rate of 0.4) after each dense layer to mitigate overfitting. The architecture starts with a dense layer of 512 neurons with ReLU activation, followed by layers of 256, 128, 64, 32, 16, and 8 neurons, each also using ReLU activation. The final output layer has a single neuron for regression output (system power prediction).

For training, the model was compiled using the Adam optimizer with a learning rate of 0.1 and configured to minimize mean squared error (MSE), while monitoring mean squared error (MSE) and MAE as metrics. Early stopping with a patience of 50 epochs was employed to prevent overfitting and ensure optimal convergence during training. After this, Grid search was applied to optimize parameters including learning rate, dropout rate, batch size, and epochs of the proposed model to improve the prediction results.

CHAPTER 2: Literature Review

2.1 Introduction

The second chapter contains a literature review that emphasizes the critical significance of energy in accelerating economic progress and emphasizes energy consumption as an important indication of a country's developmental state. Within this framework, the growth of energy engineering as a modern technical subject is acknowledged, with increasing recognition for its importance in meeting carbon reduction targets. The worldwide transition to renewable energy is a prominent issue, with many nations implementing measures to reduce pollution by lowering reliance on fossil fuels and increasing usage of renewable sources such as wind and solar. Wind energy has been hailed as a prominent player in this global transformation, having undergone enormous development and emerging as a big contributor to global energy production. Its crucial role in reducing the effects of climate change is underlined, with particular focus on the difficulties presented by changes in wind patterns brought on by climate change. The story emphasizes how accurate wind energy forecasts are essential for efficient grid management and project planning. This chapter is divided into multiple categories related to wind energy prediction based on AI, where each category contains various algorithm methodologies or other important literature associated with that group. Furthermore, the precise discussion of each category is presented to conclude. This chapter evaluates the feasibility of employing machine learning based methods for forecasting RES power output to enhance integration. The SLR identifies various successful ML approaches, including (ANNs), SVMs, Random Forests (RF), XGBoost, DTs, Logistic Regression (LR), and k-nearest neighbors (k-NN), with a notable trend toward using deep neural networks, especially Long Short-Term Memory (LSTM) network. Ensemble methods are also common for improved robustness. While ML-based predictions can enhance grid decision-making, their real-life implementation in power systems remains a topic for further research. The study suggests potential benefits in solving Unit Commitment (UC) optimization problems based on ML-based RES power predictions and emphasizes the need for future research in this direction. Figure 2-1 reflects the different categories explained in the literature.

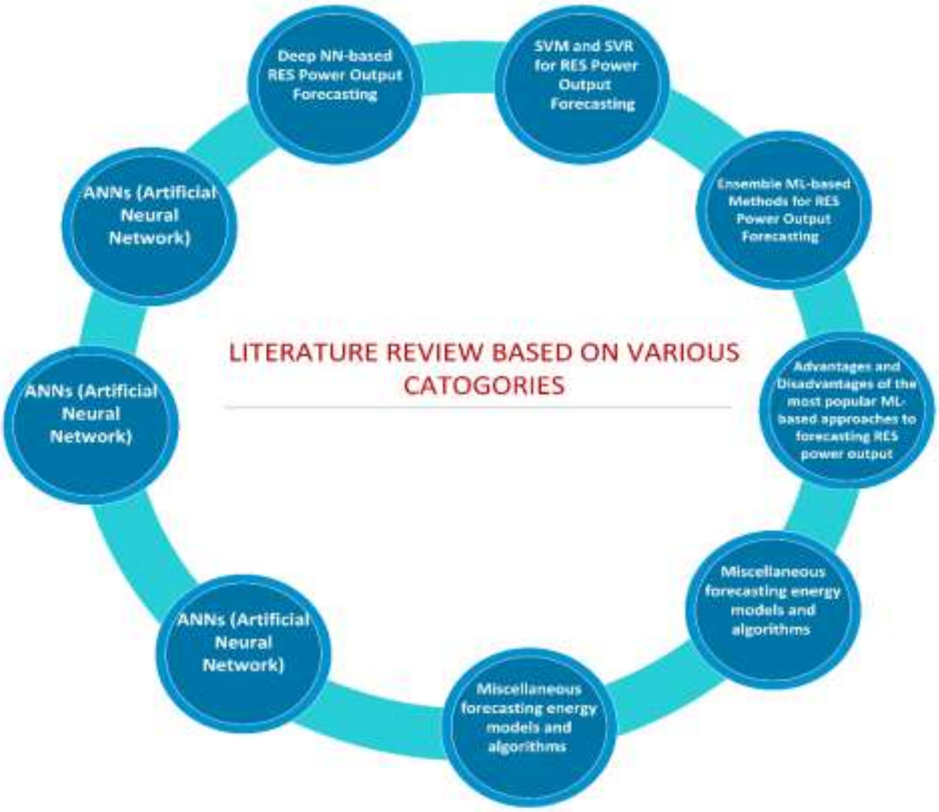

Figure 2.1: Literature review categories

The literature review chapter overviews wind energy, with a focus on AI applications, wind measurement problems, and wind prediction approaches. Finally, the GAP or future work related to that literature has been evaluated and the conclusion is given to conclude the chapter.

2.2 Contemporary Developments in Machine Learning Approaches for Predicting Renewable Energy Source Power Output

This section examines the application of Machine Learning techniques for forecasting photovoltaic (PV) and wind turbine power output. The literature evaluates various ML models, their parameters, prediction time horizons, and data collection methods. Notably, ANNs have emerged as the most popular ML-based method, with deep NNs being particularly favoured for their ability to handle non-linear features in RES forecasting. SVMs/SVRs and ensemble methods, including RF and boosting techniques, also gain attention. The analysis emphasizes short-term forecasting as predominant, with challenges noted in very short-term and long-term predictions.

Data collection primarily relies on historical on-site data, while parameters such as weather conditions significantly influence model accuracy. The ML-based model implementation involves crucial steps like data pre-processing, feature extraction, selection, hyper-parameter optimization, training, and validation. Feature selection commonly employs Principal Component Analysis (PCA) and gains importance, while hyper-parameter optimization often employs grid search and Particle Swarm Optimization (PSO). Performance measurement relies on metrics like RMSE and absolute error (MAE). Despite the importance of data pre-processing, it is often underreported in the reviewed literature. Overall, this chapter provides comprehensive insights into the current trends and challenges in ML-based RES power output forecasting.

2.3 Deep NN-based RES Power Output Forecasting

In this section, there is a clear trend toward adopting deep NNs instead of classical ANNs since they give greater generalization power, allowing big-data training to avoid arduous feature extraction and selection, decreasing computing costs and durations. According to Wang et al. [47] describe the application of Machine Learning, specifically deep learning, to forecasting renewable energy output, with an emphasis on photovoltaic and wind turbine power. It emphasizes the growing use of ANNs, particularly deep neural networks, for dealing with non-linear information. Also included are SVMs and ensemble approaches. Short-term forecasting challenges and the impact of weather conditions on model accuracy are examined. The study focuses on on-site data collection and the ML deployment process, highlighting weaknesses in reporting data pre-processing.

Deep learning is introduced as a viable strategy for dealing with intermittent and unpredictable renewable energy data, addressing the constraints of shallow models. It classifies deep learning models such as stacking auto-encoders, deep belief networks, and deep RNN, describing their advantages and disadvantages. Also, Yousif et al. [48] compare ANN strategies for predicting photovoltaic thermal (PV/T) energy production based on data from 2008 to 2017. The emphasis is on Global Solar Radiation (GSR) prediction using ANNs, including assessment factors such as MSE, MAPE, R2, RMSE, MBE, and MPE. The research covers a wide range of locales and climates, demonstrating the importance of ANNs in solar energy prediction. Various ANN architectures, including MLP, are discussed. Models with low MSE, MAPE, and high R2 values are highlighted as effective for accurate solar energy forecasts in the comparison. The report emphasizes the usefulness of ANN models for estimating GSR and offers insights for engineers and researchers working on the subject. Further, Khan et al. [49] offer DSE-XGB, a solar energy forecasting model that improves accuracy by combining ANN, LSTM, and

XGBoost. DSE-XGB regularly beats solo ANN, LSTM, and Bagging models on multiple datasets, with a 10%-12% boost in R2 value. The study used the Shapley Additive Explanation paradigm for model interpretability, emphasizing the necessity of precise solar forecasting for grid integration. DSE-XGB overcomes existing forecasting limits by utilizing the strengths of deep learning algorithms to provide exact solar PV projections. The study finishes with research recommendations and a discussion of the model's possible applications outside of solar forecasting.

Additionally, Ding et al. [50] present STL-LSTM, an ensemble framework for mid-term renewable energy generation (REG) forecasting, which is critical for grid flexibility and energy system transition. STL is used to pre-process data and extract trends and periodic patterns, whereas LSTM improves forecasting precision. The architecture is validated using monthly REG information from various renewable sources from several nations. The results demonstrate that it outperforms pure LSTM, SVR, NARNN, SARIMA, FT-LSTM, and STL-BPNN. The method is adaptable, has interpretable references, and solves the lack of mid-term REG prediction tools, making it a promising tool for improving grid flexibility throughout the energy transition.

Also, the paper [51] describes the use of LSTM Recurrent Neural Networks (LSTM-RNN) for exact PV power forecasting in smart grids. Because of the intermittent and unpredictable nature of PV output power, the growing global use of renewable energy, particularly PV systems, highlights the importance of accurate forecasting. The suggested method employs a novel methodology based on deep LSTM-RNN, which is well-known for its ability to simulate temporal variations in PV data. The paper compares five LSTM models with different topologies to three existing PV forecasting methods. The results reveal that LSTM models, particularly model 3, outperform other techniques, demonstrating the importance of deep learning in improving predicting accuracy. Further, Abdel-Nasser et al. [45] present "SUNSET," a tailored CNN for short-term solar power forecasting that addresses cloud-related uncertainties. In foggy conditions, the model achieves a forecast skill of 16.3% using hybrid input and heavy regularization. Critical elements such as sky photos and PV output histories are included in optimal input settings. Training against PV output improves performance, and judicious down sampling minimizes training time while maintaining accuracy. The findings highlight the model's usefulness for microgrids and end-users with on-site solar generation. The code is accessible for replication.

Additionally, Hussain et al. [52] describe an end-to-end hybrid network for precise PV power forecasting in microgrids. Data preparation, temporal feature extraction using a GRU sequential model, and spatial feature extraction using a CNN are the three processes in the model. The proposed model outperforms state-of-the-art approaches when tested on publicly available PV datasets, stressing the relevance of prioritizing temporal characteristics. The study emphasizes the importance of accurate PV power forecasting for optimal energy management in microgrids. Also, Feng et al. [41] explore machine learning strategies, particularly ANNs, for computing GSR in the absence of observable data. PSO-ELM (particle swarm optimization-extreme learning machine) is a new hybrid model that is presented, and its performance is compared with SVM, GRNN, M5T, and autoencoder. The study emphasizes how important accurate Rs data are in determining solar photovoltaic (PV) output. With a focus on China's Loess Plateau, it uses machine learning algorithms to forecast Rs in areas without measurements. Metrics including the Nash-Sutcliffe coefficient, relative RMSE, and MAE are used to assess the performance of the model.

After being trained with data from stations possessing measurements, the regional model is then utilized to predict in stations lacking measurements. Further, Behera et al. [42] investigate photovoltaic (PV) power forecasting, addressing uncertainties in solar generation by proposing an ELM technique. This method, integrated with incremental conductance Maximum Power Point Tracking (MPPT) using a proportional-integral (PI) controller, is optimized with PSO. The study highlights the importance of accurate PV power forecasting due to the growing integration of PV in smart grids. It categorizes forecasting models into hybrid, artificial intelligence, statistical, and physical approaches, emphasizing their role in microgrid and smart grid energy management. Evaluation metrics like RMSE, MAE and MAPE assess the proposed model's performance. The paper concludes that the ELM, particularly when optimized with accelerated PSO (APSO), surpasses other methods in short-term solar power forecasting, providing enhanced accuracy and faster convergence. Additionally, Widodo et al. [3] This research investigate a Smart Micro Grid that increases energy efficiency by combining renewable energy sources and state power plants. It seeks to lessen dependency on the state utilities by utilizing ML, Big Data, AI, IoT, and smart sensors. To achieve Future Accurate Prediction (FAP) of power consumption and renewable energy generation, the study builds a DNN with LSTM architecture, highlighting the necessity for novel machine learning techniques, particularly Deep Learning (DL).

The results demonstrate the advantage of DNN over LSTM when evaluating predictive accuracy using MAE and MSE, confirming its promise for accurate renewable energy forecasting. Furthermore, et al. [6] address the randomness and intermittent of photovoltaic (PV) power in contemporary power networks, the research presents a hybrid model for precise ultra-short-term PV power forecasting. The model combines three modules: one for feature engineering, one for error correction using wavelet transform (WT) and k-nearest neighbour (KNN), and one for point prediction using a non-pooling convolutional neural network (NPCN). The feature module tackles missing values and outliers by using an isolated forest. The error correction module lowers model variance while NPCNN concentrates on nonlinear feature extraction. The model outperforms benchmarks when evaluated using actual PV data from Limburg, Belgium, offering a novel approach to better ultra-short-term PV power forecasting. Also, Khan et al. [2] planned AB-Net to introduce a unique architecture for renewable energy (RE) forecasting to address the problem of controlling the growing power demand. The methodology includes using the AB-Net architecture, thorough pre-processing to assure data appropriateness, and gathering data from solar and wind sources.

To provide a one-step forecast of electricity generation, this design integrates a bidirectional LSTM (BiLSTM) with an autoencoder (AE). AB-Net displays state-of-the-art performance in terms of error metrics through the evaluation of benchmark datasets. Addressing data anomalies, establishing a novel hybrid network, and emphasizing short-term RE forecasting are some of the key achievements. The outcomes demonstrate AB-Net's edge over rival models and underscore its potential for precise RE power generation forecasts. Further, Liu et al. [37] propose a novel approach to short-term wind power prediction, introducing the Genetic Programming ensemble ANN to address wind power generation instability. Unlike traditional methods, GPeANN prevents error propagation by employing a semi-stochastic combination of neural networks. Tested on data from five European wind farms, the model demonstrates effectiveness with an average RMSE. Emphasizing the significance of accurate short-term WPF for reliable energy distribution, the paper contributes by creating an intelligent ensemble predictor that enhances robustness and outperforms individual predictors. The ensemble methodology, utilizing Genetic Programming, creates a nonlinear decision space, improving the model's adaptability to meteorological fluctuations for more reliable wind power predictions.

2.3.1 Discussion

The research consistently argues that advanced neural network models, particularly deep neural networks (DNNs), outperform classic ANNs in the domain of renewable energy forecasting, with a particular emphasis on solar and wind power. The included studies, which range from DSE-XGB to STL-LSTM, SUNSET, and AB-Net, demonstrate the usefulness of hybrid models, which combine techniques such as ANN, LSTM, and ensemble approaches such as Genetic Programming. These models outperform traditional approaches consistently, underlining their capacity to improve accuracy and reliability in projecting renewable energy generation. The findings highlight the increasing importance of advanced neural network topologies and ensemble methodologies in improving the precision of renewable energy projections, providing vital insights for future advances in the field.

2.4 SVM and SVR for RES Power Output Forecasting

According to Zendehboudi et al. [53] explore the transition from traditional fossil fuels to renewable energy, notably solar and wind power. It underlines the difficulties in projecting these renewable resources accurately and criticizes established methods. The research focuses on the usefulness of SVM models in solar and wind energy forecasting, and it is supported by a systematic review of 75 relevant publications published between 2009 and 2017. Descriptive statistics show how these articles and SVM applications are distributed in various contexts.

The SVM modelling approach is classified, and applications in predicting solar radiation and wind speed are investigated. The limitations and methodological constraints of SVM modelling are acknowledged in the paper. It finishes by outlining research gaps and recommending more studies into hybrid models for improved accuracy. Further Lin et al. [54] use an improved Moth-Flame Optimization-SVM(IMFO-SVM) model to enhance the prediction accuracy of photovoltaic (PV) power generation. The study adds new features to the moth-flame optimization technique, enhancing diversity while balancing search capabilities. When the model's efficacy is evaluated using actual data from an Australian photovoltaic power plant, it outperforms other models in terms of optimization. The work adds a trustworthy model for real-time grid dispatching and power system stability and emphasizes the significance of accurate PV output projections in the context of the world's transition to sustainable energy sources. Additionally, Li et al. [55] introduce a hybrid IDA-

SVM model for short-term wind power prediction, which addresses the issues provided by wind power's non-stationary and stochastic character.

To boost prediction accuracy, the model combines the SVM with an improved dragonfly algorithm (IDA). When tested on real datasets from the La Haute Borne wind farm in France, the IDA-SVM model outperforms other models such as back propagation neural networks and Gaussian process regression. Accurate forecasting of short-term wind output is critical for effective integration into power grids, and the suggested model provides a possible solution.

2.4.1 How SVM, SVR used of PV

SVM and Support Vector Regression (SVR) are advanced machine learning techniques extensively applied in Photovoltaic (PV) systems to enhance performance, reliability, and efficiency [43].

SVM, a classification algorithm, is pivotal in fault detection and classification within PV systems. It processes data patterns from PV panels to differentiate between normal operational states and various fault conditions such as short-circuits, open-circuits, or shading issues. By training on labelled datasets representing different fault types, SVM can accurately identify and classify these anomalies, enabling prompt maintenance actions. Additionally, SVM is used for performance monitoring by classifying the system's operational data into distinct categories, thereby identifying deviations from expected performance that might suggest underlying issues [56].

On the other hand, SVR, a regression algorithm, excels in predicting continuous variables like power output, which is essential for effective energy management in PV systems. By training on historical data encompassing inputs such as solar irradiance, temperature, and time of day, SVR learns the relationship between these factors and the power output. This enables SVR to predict future power output with high accuracy, facilitating better planning and optimization of energy supply. Furthermore, SVR is instrumental in forecasting energy production based on past weather patterns and system performance, aiding in grid integration and ensuring a reliable energy supply [7].

SVR is also employed in efficiency analysis to assess how efficiently PV systems operate under varying environmental conditions. By modelling the relationship between environmental factors and power output, SVR helps in identifying performance trends and potential areas for improvement. This continuous efficiency analysis is crucial for maintaining optimal system performance over time [29].

Both SVM and SVR offer significant benefits due to their high accuracy and robustness. They effectively handle non-linear relationships and are resistant to overfitting, especially in high-dimensional spaces. This makes them suitable for complex datasets commonly encountered in PV systems. The versatility of SVM and SVR, enabling their application in both classification and regression tasks, adds to their value in comprehensive PV system analysis [37].

2.4.2 Discussion

The review of the literature highlights the significant shift from conventional fossil fuels to renewable energy, with a focus on solar and wind power. The research emphasizes the difficulties in precisely estimating these resources, underlining the limitations of existing approaches. With insights from a systematic review and a recommendation for more research into hybrid models, SVM models prove useful in solar and wind energy forecasting. The adoption of the IMFO SVM model improves the accuracy of PV power generation estimates, providing a dependable tool for real-time grid dispatching. Similarly, the hybrid IDA-SVM model handles the non-stationary and stochastic nature of wind power, giving an efficient solution for forecasting short-term wind output. These studies emphasize the magnitude of advanced modelling techniques and hybrid models.

2.5 Ensemble of ML-based Methods for RES Power Output Forecasting

According to Lahouar et al. [57] introduce a direct hour-ahead WPF model employing the RF method. It focuses on selecting key meteorological factors, specifically spatially averaged wind speed and direction. RF, known for its ability to handle non-linear relationships without extensive tuning, was chosen. Using data from the Sidi Daoud wind farm in Tunisia, the study shows enhanced forecast accuracy compared to classical neural network predictions. The research underscores the importance of wind speed and direction in optimizing model performance, showcasing RF's resilience to irrelevant inputs. Overall, the paper highlights RF's potential for improved WPF through the effective utilization of additional information.

Also, Tato et al. [56] focus on leveraging machine learning, namely the RF algorithm, to enhance solar energy forecasting. The study examines three years' worth of data from six solar PV modules in Faro, Portugal, integrating Smart Persistence, irradiance, and historical production data. A variety of data elements are combined in the suggested feature set for both training and validation. The best panels achieve an NRMSE of 0.25, indicating that the use of Smart Persistence as a machine learning input greatly improves short-term forecast accuracy. The study highlights how RF are helping to improve solar energy forecasts, which is important for solar power plants to remain competitive.

Furthermore, Zameer et al. [58] a wind power prediction methodology using a genetic programming-based semi-stochastic combination of various neural network types, including feed-forward backpropagation neural networks (FFBPNNs), radial basis function neural networks (RBFNNs), backpropagation neural networks (BPNNs), and Broyden-Fletcher-Goldfarb-Shanno neural networks (BFGSNNs). This ensemble approach aimed to forecast wind power output by collectively considering the predictions of different neural network models. The study demonstrated the effectiveness of this method in addressing the inherent instability of wind power generation, attributed to atmospheric and meteorological variables. The approach was found to create a robust decision space, reducing errors caused by individual base learners and enhancing overall prediction performance, especially in response to sudden input changes.

Additionally, Wang et al. [11] combine BPNNs, RBFNNs, and SVMs for wind power output forecasting, and a Bayesian model averaging (BMA) technique was used. The method created variety by combining several machine learning models with self-organizing map (SOP) clustering and k-fold cross-validation to construct three training subsets for meteorological data. The results revealed that the SOP-based technique outperformed equivalent state-of-the-art alternatives in accurately and dependably projecting wind power generation under diverse meteorological conditions. Also, AlKandari et al. [44] present a hybrid model “MLSHM” exact solar power prediction in renewable energy facilities, is introduced. Theta statistical approach is combined with machine learning (LSTM, GRU, Auto-LSTM, Auto-GRU) to improve accuracy through structural and data diversity. The ensemble employs averaging and variance combination methods. The dataset used for experiment shows that MLSHM outperforms individual models, stressing the combination of machine learning and statistical techniques [41], [53] . The study emphasizes the significance of diversity in ensemble methods for improved predictions in renewable energy applications [59].

2.5.1 Discussion

In discussion, the above literature demonstrates the effectiveness of machine learning, particularly RF and ensemble approaches, in improving wind and solar energy forecasting. These approaches improve accuracy, especially when Smart Persistence and different data components are considered. The research brings vital insights by providing effective algorithms and hybrid models that have the potential to improve the dependability and sustainability of renewable energy systems.

2.6 Advantages and Disadvantages of the most popular ML-based approaches to forecasting RES power output

The fundamental issue in forecasting Renewable Energy Sources (RES) power output is successfully modelling both its autoregressive temporal characteristics and its reliance on uncertain, non-linear atmospheric spatial variables. To address these problems, several machine learning algorithms discussed in the Systematic Literature Review (SLR) adopt different strategies. Each method has advantages and disadvantages, and there is no universal solution. The method of choice is determined by criteria such as the specific application, available data, and resources. Table 2.1 summarizes the primary advantages and disadvantages of commonly used ML-based techniques for forecasting photovoltaic (PV) and wind output. It also recommends the best uses for each strategy.

Table 2.1 Comparison of Machine Learning Approaches for RES Power Output Forecasting

Approach	Advantages	Disadvantages	Application
Traditional ML-based models			
ANN	• Can learn non-linear relationships.	• Hand-engineered feature selection. • Fail to learn complex patterns from intermittent, stochastic, and highly varying data. • Sample complexity: Network instability and parameters non-convergence when dealing with huge amounts of training data. • Time-consuming training phase.	RES power output forecasting within stationary frameworks.
SVM/SVR	• Well-suited for complex non-linear applications. • Robust to noisy and biased data. • Less prone to overfitting than other ML-based methods. • Good generalization capability for small datasets.	• Highly sensitive to hyper-parameter tuning.	Newly built PV or wind plants, which lack large amounts of historical data.
Deep NNs			
LSTM	• Automatic feature selection. • Can handle time series data. • Can handle long-term time dependencies. • Can capture complex patterns in sequential data.	• Prone to overfitting. • Sensitive to hyper-parameter tuning. • Computationally expensive.	RES power output forecasting considering autoregressive features (time series).

	• More robust than simple RNN to noisy and missing data.		
CNN	• Automatic feature selection. • Accurate modeling of spatial features.	• Requires large amounts of data to lean. • Computationally expensive.	• PV power output forecasting based on sky or satellite images. • Spatial feature modeling for weather-related data.
Ensembles			
RF	• Robust to missing data and outliers. • No need for variable selection. • Can handle large datasets. • Can handle high-dimensional data. • Easy hyper-parameter tuning. • Less prone to overfitting than other ML-based methods.	• Not suitable for low-dimensional data. • Not suitable for small datasets.	RES power output forecasting within the context of high-dimensional, large datasets.
Different base learners	• Reduce overfitting. • Robust to base learners' errors. • Robust to inconsistencies in the changing weather data. • Better performance than traditional ensembles. • Improve of individual ML-based models.	• Computationally expensive. • Depend on the combination strategy.	RES power output forecasting within highly complex scenarios.

2.7 Miscellaneous forecasting energy models and algorithms

Further Demolli et al. [8] focus on machine learning techniques for long-term wind power forecasts utilizing daily wind speed data. The study suggests a technique for predicting wind power that considers the daily mean wind speed and standard deviation and uses five machine learning algorithms (LASSO, kNN, xGBoost, RF, and SVR). The models are put to the test in a variety of settings, showing their universal applicability. The outcomes show that RF, SVR, and xGBoost are all successful, RF performed the best. The study concludes that machine learning algorithms can be used effectively to anticipate wind power before building new wind farms. Also, Zhou et al. [10] integrate WPD and LSTM networks to create a hybrid deep-learning model for PV power forecasting one hour ahead of time. Breaking down the series using WPD and using the sub-series as input for LSTM networks, solves the problems associated with PV power interruption. After reconstruction, the results are linearly weighted. PV power forecasting becomes more accurate and stable when evaluated using Alice Springs data, as it performs better than when using individual LSTM, RNN, GRU, and MLP models. Additionally, Ahn et al. [12] uses real-time on-site meteorological IoT data to propose a deep RNN model for short-term PV power forecasting.

The experimental results surpass standard models such as ARIMA and SVR-RFN, demonstrating good accuracy for forecasts of 1-3 hours (92.9%-94.8% normalized RMSE) and 5-15 minutes (96.6%-98.0% normalized RMSE). highlights how crucial real-time data is to accurate short-term PV forecasting. Future upgrades will include the incorporation of more meteorological features and techniques for abnormality detection. Further Torres et al. [13] propose a novel deep learning-based method for solar photovoltaic (PV) power prediction using the H2O R package. It takes a multi-step approach to managing large amounts of time series data. Assessments conducted on solar PV data from Australia demonstrate competitive performance in comparison to well-established algorithms, highlighting the benefits of scalability for large datasets when compared to alternative methods that incur exponential time increases. According to Agga et al. [14] hybrid CNN-LSTM model for short-term PV energy forecasting outperforms traditional machine learning and standalone deep learning models in terms of accuracy and stability. The CNN-LSTM architecture, which can evaluate spatial and temporal data, is effective when applied to real data from Rabat, Morocco. The study emphasizes the importance of accurate PV estimates for grid stability and system integration. The model shows promise for improving power system operations, with further study focusing on potential applications in larger renewable energy predictions and consumer behaviour analysis.

Further, Cebekhulu et al. [15] evaluated six well-known machine-learning algorithms for power demand and supply prediction in smart grids. After thorough fine-tuning, the models were tested on Eskom's datasets, revealing little to no significant difference in their performance, except for challenges in predicting wind power. The findings suggest that, with proper tuning, any of these algorithms can be deployed for prediction in smart grid systems, emphasizing the importance of reporting multiple metrics. Further research is encouraged, especially in addressing challenges related to stochastic energy sources like wind power. Also, Vennila et al. [16] provide a hybrid approach that combines machine learning and statistical methodologies to provide precise solar power predictions in large-scale renewable energy plants.

When compared to previous methods, the hybrid approach's ensemble of machine learning models offers higher accuracy and cost savings. The hybrid approach beats others that rely primarily on machine learning in managing market volatility and intermittent sources, emphasizing the importance of understanding weather patterns. The suggested feature selection method combines filter and wrapper techniques, leveraging ensemble feature classification for improved estimates of solar power generation. Overall, the study emphasizes hybrid models' potential for greater performance and accuracy in renewable energy forecasting. Additionally, Mahmud et al. [17] compared techniques such as Linear Regression, Polynomial Regression, Decision Tree Regression, SVR, RF Regression, LSTM, and MLP, this study conducted in Alice Springs, Australia, focuses on machine learning for PV power forecasting. The RF Regression shows better results. The influence of weather characteristics, including temperature and relative humidity, is examined, with a focus on data standardization to enable more accurate forecasts. Planning for energy generation can benefit from the new insights, but large-scale forecasting and panels with MPPT require more study.

According to Zheng et al. [19] hybrid framework for precise power generation forecasting in multiple renewable sources. It combines a CNN, Attention-based Long Short-Term Memory (A-LSTM), and Auto-Regression for energy correlation, nonlinear temporal, and linear temporal patterns. Validation on a real renewable energy system demonstrates its superior accuracy compared to other models, notably reducing MAE for solar PV, solar thermal, and wind power. The study emphasizes the importance of energy correlation patterns, addressing the critical need for enhanced multi-energy generation predictions in efficient power scheduling for renewable systems. Furthermore, Rahman et al. [21] discuss the use of ANNs for renewable energy prediction, particularly focusing on their popularity due to good predictive ability.

The study recommends ANNs, emphasizing the importance of network structure, learning procedures, and various parameters for energy prediction. It underscores challenges such as theoretical complexity, model optimization, and the need for domain experts. The conclusion highlights the benefits of ANNs, including adaptive learning and real-time operation, while suggesting future directions like exploring advanced AI techniques and incorporating IoT tools in renewable energy research. Additionally, Wan et al. [25] present ANNs to the forecast of renewable energy is covered in this section, with an emphasis on how well-liked ANNs are for this reason. The study suggests ANNs, highlighting the significance of different parameters, learning processes, and network architecture for energy prediction. It draws attention to difficulties such as theoretical complexity, model optimization, and the requirement for subject matter specialists. In addition to highlighting the advantages of ANNs, such as adaptive learning and real-time operation—the conclusion makes suggestions for future research topics, such as investigating more sophisticated AI methods and utilizing IoT tools in the study of renewable energy.

Also, Laiet al. [29] examine the machine-learning models for renewable-energy forecasts, this paper places special emphasis on parameter selection, data preparation, model selection, and performance indicators. It emphasizes how important precise forecasts are becoming in response to climate change. The study observes a rise in the application of hybrid models and artificial intelligence, especially in the prediction of solar and wind energy. Important conclusions include the frequent use of extreme-learning machines and support-vector machines for parameter selection, as well as the predominance of decomposition approaches in data pre-processing. Future objectives for research include going beyond solar and wind predictions, examining the effects of data pre-processing, and developing novel parameter selection metaheuristics. Furthermore, Niu et al. [33] provide an AGRU model for multi-step-ahead WPF. The model uses GRU blocks to add a correlation between forecasting stages and an attention mechanism to choose features. When compared to benchmarks, validation using case studies shows enhanced forecasting accuracy, computational efficiency, and feature selection capabilities. The study guides choosing models in multi-step-ahead forecasting and emphasizes the need for accurate WPF for dependable power system operations.

Additionally, Hong et al. [35] works in the field of energy forecasting are given in this article, with a focus on relevant data sources, repeatable research, and suggestions for publishing high-calibre publications. It covers a wide range of topics, such as renewable energy, long-term load predictions, and electricity pricing. By examining cutting-edge subjects including artificial intelligence, ensemble techniques, and prediction valuation, the paper emphasizes the significance of interdisciplinary cooperation in energy forecasting. Also, Zhao et al. [18] perform a study that investigates how energy engineering employing resources such as wind and solar aids in pollution reduction and economic growth. They discussed how important it is to forecast how much electricity the wind will produce and agreed that using AI will allow them to make better predictions. Furthermore, K. Nam et al. [26] create a custom forecasting model for renewable energy systems to predict changing electricity demand and generation. Different scenarios are assessed using the best-performing model, GRU. While GRU excels at predicting rapid changes, it may struggle with detecting long-term patterns compared to more complex models. Moreover, Zhao et al. [24] focused on the intelligent and hybrid methods that use big data for accurate predictions.

The study provides an outline of big data and AI's role in wind energy forecasting, including data sources, pre-processing, and machine learning algorithms. However, the research is restricted by its scope and lack of focus on unstructured data. Additionally, Tarek et al. [22] present SFSPSO, a novel optimization technique merging PSO and SFS for LSTM parameter optimization, leading to improved model performance compared to existing methods; however, further investigation is required to validate its efficacy on larger datasets According to ELSARAITI et al. [28] use LSTM to estimate short-term solar PV generation. The use of LSTM for time series prediction has the benefit of capturing detailed temporal patterns and dependencies in data, but it is more complicated and requires more training time.

2.7.1 Discussion

In essence, the literature emphasizes the accuracy with which machine learning and hybrid models, such as RF and CNN-LSTM, anticipate wind and solar energy parameters. Notably, these models show adaptability, pre-construction wind power potential, and increased solar energy prediction accuracy. Real-time meteorological IoT data is critical in short-term PV power forecasting, highlighting the significance of real-time data in effective predictions. The intricacy of parameter selection, the complexities of data preparation, and the requirement for successful model selection are all challenges. The literature adds to the growing landscape of renewable energy forecasting by emphasizing the importance of advanced AI algorithms and the continuous emphasis on real-time data for future research objectives.

2.8 ANNs

Further Yousif et al. [60] conduct a comprehensive review and comparative investigation of Photovoltaic/Thermal (PV/T) energy data prediction systems, with a particular emphasis on the use of various ANN methodologies. The study collects and assesses data from varied geographical places with robust meteorological stations throughout the decade (2008-2017). The goal is to improve the efficiency of solar energy systems by utilizing ANNs to anticipate GSR. Recognizing the difficulties posed by environmental elements such as temperature, dust, and humidity, the study offers the novel concept of PV/T hybrids, which combine photovoltaic modules with solar thermal collectors to offset the negative impacts on PV module performance. The methodology employs ANNs for GSR estimates due to their ability to handle nonlinear data like human cognitive processes.

To assess the accuracy of ANN models, evaluation measures such as MSE, RMSE, MAPE, and R-squared (R2) are used. The research includes a geographical and climatic variation analysis, which provides insights into the adaptability and performance of ANN models in a variety of environmental situations. The conclusion underlines the appropriateness of ANN models for GSR prediction in PV/T systems and gives useful recommendations for researchers and engineers interested in using ANNs to generate solar energy data. The working procedure of the ANN is given in Figure 2.2.

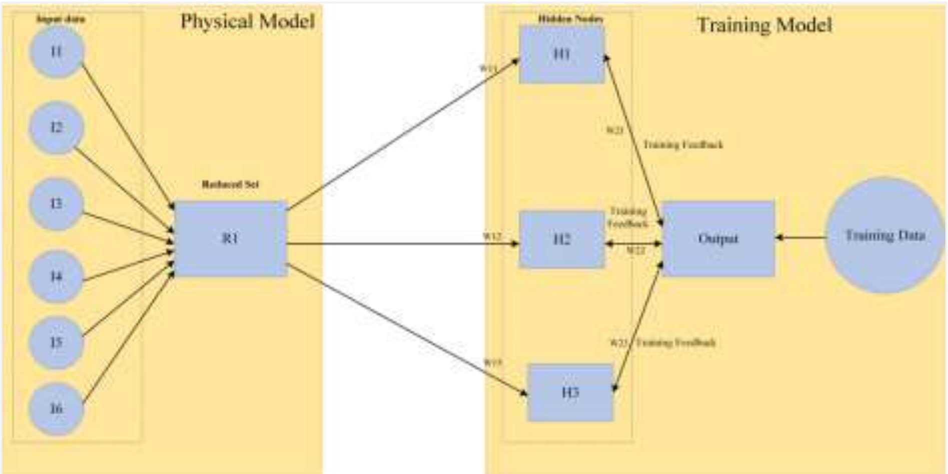

Figure 2.2: Working procedure of ANN

According to Wang et al [47] the main highlights are below. Among them, the following ones should be highlighted:

- Hand-engineered feature selection: ANN feature selection not only requires significant personal experience but also prevents traditional ANNs from dealing with inherently non-linear features, as in the case of RESs.
- Time-consuming training phase.
- Limited generalization capability: Traditional ANNs fail to learn complex patterns from intermittent, stochastic, and highly varying data, such as weather data.
- Sample complexity: ANNs will suffer from network instability and parameters non-convergence if, due to the increasing availability of environmental meters, huge amounts of training data related to RESs are available. The percentage of the deep ANN, ELM and other learning model is given in Figure 2.3.

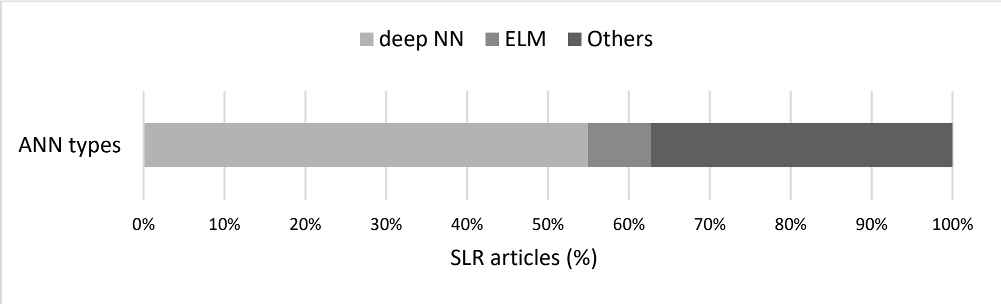

Figure 2.3: Most used types of artificial neural networks

Additionally, Huang et al. [61], The ELM, a unique approach for Single-Hidden Layer Feedforward Neural Networks (SLFNs), is introduced in this research. ELM seeks to address traditional neural networks' slow learning pace by randomly assigning input weights and hidden biases, hence reducing repetitive tweaking. The methodology demonstrates that this random assignment is feasible under specific conditions. ELM considers SLFNs to be linear systems, calculating output weights analytically. This method produces learning speeds hundreds of times faster than traditional methods, as well as high generalization performance. The report emphasizes ELM's simplicity, efficiency, and prospective applicability in a variety of sectors, demonstrating improved performance in benchmark testing compared to older approaches.

Furthermore, Ding et al [62] introduce the ELM, a learning technique for single hidden layer feedforward neural networks, stressing its benefits in terms of training speed and overfitting resistance. The methodology entails a thorough examination of theoretical foundations, algorithmic concepts, and applications. The authors explain the history of neural networks, emphasizing ELM's versatility and fast learning rate. The algorithm's primary characteristics are adaptive hidden layer node placement and random weight and bias assignment, allowing for quick learning in a single cycle. Several extensions, such as online sequential ELM and pruned ELM, are described to meet specific issues. Experiments compare ELM to other algorithms, with future research plans and funding assistance acknowledged. Types of deep NN are given in Figure 2.4.

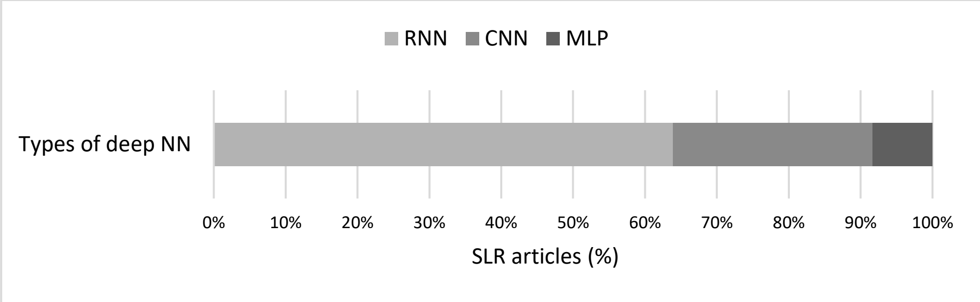

Figure 2.4: Most popular architectures used for deep NNs

2.8.1 Discussion

ANNs have shown effectiveness in solar energy prediction, the ELM stands out as a promising improvement, delivering a faster learning rate and improved performance. The findings pave the way for future research aimed at refining and increasing the use of ELM as well as overcoming the noted difficulties in standard ANN approaches, ultimately contributing to the progress of solar energy prediction systems.

2.9 Ensemble Methods

According to Chen et al. [63], the increasing trend for using deep NNs discussed in Section, ensemble methods have also been identified as one of the most popular ML-based techniques among the SLR articles. Whereas 37.8 % of them are devoted to the former, 19.51 % proposed the latter. Ensemble methods use multiple learning algorithms – called base learners – to improve the predictive performance corresponding to the use of individual learning algorithms. RF is an ensemble of DTs, focused on increasing the diversity among the trees to enhance its prediction performance. In addition to its very good discriminative capability, RF can manage large databases, handle a great number of input variables without performing variable selection, deal with missing data and outlier removal, and avoid overfitting.

Boosting techniques, including Gradient Boosting (GB) and Extreme GB (XGBoost), are also ensembles of DTs. In GB, additive regression models are built by fitting them according to the residuals' least square minimization. Furthermore Friedman et al. [64]. One of the main advantages of GB algorithms is their flexibility; they allow to optimize different loss functions and provide several options for hyper-parameter tuning. The XGBoost algorithm extends the GB one by providing customizable optimisation objectives and evaluation criteria, as well as allowing regularisation, which helps to reduce overfitting. Also, LEE et al. [65] focus on forecasting wind power generation to effectively integrate it into smart networks. For reliable predictions, ensemble learning methods such as Boosted

Trees, RF, and Generalized RF are used. Using wind turbine data from France and Turkey, the models are compared to Gaussian process regression and SVR. Ensemble models outperform isolated models, demonstrating their efficacy. Lagged variables are found to contribute significantly to model accuracy.

2.10 Compared other methods like PV systems.

Comparing photovoltaic (PV) power systems with other renewable energy methods involves examining various factors such as efficiency, cost, environmental impact, and scalability. Here's a comparison with some other common renewable energy sources [42]:

2.10.1 Photovoltaic (PV) Power Systems:

- Efficiency: PV systems convert sunlight directly into electricity using semiconductor materials like silicon. The efficiency of commercial PV panels typically ranges from 15% to 22%.
- Cost: The cost of PV systems has been decreasing over the years due to advancements in technology and increased production scale. Initial installation costs can be high, but operational costs are low.
- Environmental Impact: PV systems produce no direct emissions during operation. However, there are environmental considerations during the manufacturing and disposal of panels.
- Scalability: PV systems can be scaled from small residential installations to large utility-scale solar farms [52].

2.10.2 Wind power

- Efficiency: Modern wind turbines convert about 35-45% of the wind's kinetic energy into electricity. The efficiency can vary based on location and wind conditions.
- Cost: Wind power has become more cost-competitive with other energy sources. Initial installation costs are high, but operational costs are relatively low.
- Environmental Impact: Wind power produces no direct emissions, but there are concerns about noise, visual impact, and effects on wildlife, particularly birds and bats.
- Scalability: Wind power can be implemented onshore and offshore, with capacities ranging from small single turbines to large wind farms [57].

2.10.3 Hydropower

- Efficiency: Hydropower plants are highly efficient, converting about 90% of the available energy into electricity.
- Cost: Hydropower can be cost-effective over the long term, but the initial construction costs are high, especially for large dams.
- Environmental Impact: Hydropower can have significant environmental impacts, including habitat disruption, changes in water quality, and displacement of local communities.
- Scalability: Hydropower is typically large-scale, although small and micro-hydro installations are also possible [53].

2.10.4 Biomass Power

- Efficiency: The efficiency of biomass power plants varies but is generally lower than other renewables, often around 20-30%.
- Cost: Biomass can be cost-effective depending on the availability of feedstock. Costs include collection, transportation, and processing of biomass.
- Environmental Impact: Biomass is considered renewable if managed sustainably, but it does produce emissions. However, it can also help manage waste.
- Scalability: Biomass power can be scaled to various sizes, from small local plants to larger industrial operations [54].

2.10.5 Geothermal Power

- Efficiency: Geothermal plants can achieve efficiencies of around 10-20%, but they provide a stable and continuous power supply.
- Cost: High initial costs due to drilling and exploration, but low operational costs once the plant is running.
- Environmental Impact: Geothermal power has minimal emissions, but there can be concerns about land use and water quality.
- Scalability: Geothermal power is location-specific, typically feasible in regions with significant geothermal activity [50].

2.10.6 Analysis

- Efficiency: Hydropower and wind power are generally more efficient than PV and biomass.
- Cost: Wind and PV have become increasingly cost-competitive. Hydropower and geothermal have high initial costs but low operating costs.

- Environmental Impact: All renewables have minimal emissions, but each has unique environmental considerations.
- Scalability: PV and wind are highly scalable. Hydropower and geothermal are more location dependent [51].

The research underlines the significance of precise wind power forecasts in solving issues in power grid dispatch and wind turbine economic management. Despite the positive results, it is proposed that future work investigate multiscale ensemble models and add spatiotemporal information for further improvement. Also, Khan et al. [66] Gathering historical SCADA data, operational records, and system alerts from a 3 MW direct-drive turbine is the proposed methodology, with stator temperature as the goal variable. A two-layer ensemble model is trained using thorough pre-processing, including optimal feature selection and managing null values. The first layer combines RF, Extra Tree Regressor, and XGBoost models, while the second layer, which serves as the meta layer, also uses an XGBoost model. Model performance is assessed using validation metrics focusing on RMSE, with a threshold for anomaly detection based on established limitations. The model's accuracy in detecting turbine defects is confirmed using rigorous metrics and graphical approaches. Future research could investigate fault type classification algorithms, false alarm likelihoods, and a thorough grasp of generic fault differences. Furthermore, Matinet al. [67] In this study, machine learning techniques are used to estimate wind speed and power production in a Supervisory Control and Data Acquisition (SCADA) system. For this objective, six algorithms are used: Light GB Machine, GB Regressor, Ada Boost Regressor, Elastic Net, Lasso, and an ensemble of Light GB Machine and Ada Boost. The models are trained and tested using 10-fold, 5-fold, and 4-fold cross-validation methods, and their performances are compared. Root-Mean-Square Error (RMSE), MAE, MAPE, and coefficient of determination (R2) are among the evaluation measures.

The results show that the ensemble technique predicts the SCADA system's production power more accurately, as shown by lower RMSE values and higher R2 coefficients. The computational efficiency and accuracy of the suggested methods in forecasting wind-related parameters are evaluated. The study intends to improve the prediction capacities of machine learning models for SCADA systems, notably in renewable energy applications. Furthermore, Ramon et al.[68] Using data from a wind farm in Parazinho, Brazil, the study applies a thorough technique for short-term wind energy forecasting. The wind power generation data is first submitted to Complete Ensemble Empirical Mode Decomposition

(CEEMD), which divides it into five Intrinsic Mode Functions (IMFs) and a residue. Lagging approaches and three separate procedures are used in pre-processing: Box-Cox Transformation (BC), Correlation Matrix Analysis (CORR), and PCA.

The ensemble learning method combines basic models such as k-nearest Neighbours, Partial Least Squares Regression, Ridge Regression, and SVR with a meta-model known as Cubist Regression. Stacking-ensemble learning is implemented in two layers, the first of which combines individual predictions from base models and the second of which uses pre-processed predictions as input for Cubist Regression. The models undergo training with 5-fold cross-validation, and their performance is assessed using MAE, MAPE, and RMSE. Statistical tests, specifically the Diebold-Mariano (DM) test, are employed for comparing forecasting errors among different models. The study systematically compares the proposed approach with variations in pre-processing techniques, decomposition methods, stacking-ensemble models, and non-decomposed models. The chosen model for each scenario is determined based on its accuracy and stability. Future research directions include hyperparameter optimization, testing additional models in stacking approaches, exploring different decomposition methods, and incorporating dual decomposition methods in stacking-ensemble learning. Furthermore, Piotrowski et al. [69] focused on projecting power generation for tiny wind turbines, with a 48-hour prediction horizon in mind.

The study aims to fill a knowledge gap, particularly for prosumer-owned turbines that face specific obstacles. The study looked at wind speed forecasts with a 48-hour horizon, which is a rarely studied issue. Various prediction algorithms, including machine learning techniques such as LSTM, MLP, SVR, and KNNR, were used. The research presented hybrid and ensemble approaches, which merged physical models with single procedures. MAE, RMSE, R, MBE, PCTL75AE, and PCTL99AE were among the evaluation criteria. Forecasts were classified according to the variables employed into several input data classes. The supplied data was divided into three sets: training, validation, and test. The data from the second year served as the test set for the final evaluation. The performance of single methods, hybrid methods, and ensemble methods was highlighted for each input data class. The findings shed light on the efficacy of various models and methods, stressing the impact of input data complexity on forecast accuracy and identifying the most successful approaches for forecasting small wind turbine energy generation.

2.10.7 Discussion

The examined literature demonstrates the expanding importance of ensemble approaches, notably in the field of machine learning-based wind power generation forecasting. Ensemble techniques, such as RF, GB, and Extreme GB, have emerged as robust approaches, outperforming individual models in studies from Chen et al. [44], Khan et al. [47], Matin et al. [48], Ramon et al. [49], and Piotrowski et al. [50]. Notably, these ensemble approaches show adaptability in dealing with the different issues inherent in wind energy forecasting, including managing huge datasets, supporting several input variables without the requirement for variable selection, and efficiently dealing with missing data and outlier removal.

Lagged variables are discovered as major contributions to model accuracy, stressing the need to include them in models. Ensemble approaches are especially useful in Supervisory Control and Data Acquisition (SCADA) systems, as demonstrated by the combination of Light GB Machine and Ada Boost for enhanced accuracy in estimating production power. While the good results are clear, the literature also suggests future study directions, such as investigations into multiscale ensemble models, the incorporation of spatiotemporal information, and the examination of fault-type classification methods. Overall, the findings highlight the importance of ensemble approaches in improving the precision and reliability of wind power generation estimates, with a strong call for more investigation and refinement in addressing specific difficulties.

2.11 Finding and GAP

a) Based on the literature, the research highlights the effectiveness of hybrid models and ensemble techniques in refining renewable energy forecasting, there is still a need for additional exploration and comparison of various hybrid architectures and ensemble methodologies. To acquire even higher accuracy and resilience, research might focus on enhancing the combination of several machine learning algorithms and ensemble techniques.

b) The significance of real-time data in renewable energy forecasting is emphasized, the literature does not go into detail about how to overcome the barriers involved with getting and processing real-time data. Future studies could investigate approaches and technologies for collecting, processing and combining real-time data into forecasting models.

c) Parameters selection and model evaluation are crucial for enhancing the performance of deep learning models related to wind energy prediction. Effective parameter selection involves tuning hyperparameters such as learning rates, batch sizes, and network architecture, which significantly affects model outcomes. Manual tuning is often impractical due to the extensive search space, making automated techniques like Grid Search, Random Search, and more advanced methods such as Bayesian Optimization or Genetic Algorithms essential. Data preparation also plays a pivotal role, as issues such as missing values, normalization, and augmentation need to be meticulously handled to avoid overfitting or underfitting. Developing standardized data preprocessing pipelines and employing robust data augmentation strategies can enhance model performance. Model evaluation, meanwhile, requires rigorous metrics and validation methods to accurately assess model efficacy and avoid problems like overfitting. Comprehensive evaluation protocols, including cross-validation and diverse metrics, alongside techniques such as ensemble learning, can provide a clearer picture of a model's capabilities. Future research should focus on creating standardized protocols and automated systems for parameter tuning, data preparation, and model evaluation to streamline these processes. Additionally, a comprehensive framework that integrates advanced deep learning techniques with thorough hyperparameter optimization is necessary to precisely predict wind turbine energy output. This holistic approach will ensure more accurate and reliable results in practical applications.

d) Several studies report decisions based on specific geographical locations, and there is a need for research that verifies models across different regions with varying climatic conditions. This would improve model generalizability and usefulness in varied scenarios, so developing a model such a model which can used in various geographical locations can be a future study.

e) The literature focuses on short-term and mid-term forecasting, but there is a study void in ultra-short-term forecasting, which is critical for grid stability and management. Methods for exact ultra-short-term predictions, remarkably for rapid changes in energy generation, are being researched.

f) Model generalization in wind energy forecasting using deep learning involves ensuring that a model performs effectively on new, unseen data beyond its training set. This concept is crucial because models that overfit may excel on training data but fail to predict accurately in real-world applications. Overfitting occurs when a model learns specific patterns or noise in the training data that do not apply to other datasets. Conversely, underfitting happens when the model is too simplistic to capture the underlying patterns, resulting in poor performance across both training and new data. A significant challenge is geographic and temporal variability. Wind patterns can vary widely due to geographical differences such as topography and proximity to bodies of water, and due to temporal factors like seasonal and diurnal changes. Models trained on data from a specific region may not perform well in different locations or under different conditions. To mitigate this, incorporating diverse datasets that cover a range of geographic and weather conditions is essential. Techniques such as data augmentation, which involves simulating various scenarios or introducing controlled noise, can enhance model robustness.

Model complexity also plays a role in generalization. Deep learning models with many parameters can capture intricate patterns but are at risk of overfitting. Regularization techniques like dropout, weight decay, and early stopping can help in balancing complexity and generalization. Additionally, transfer learning using pre-trained models on related tasks and fine-tuning them can leverage existing knowledge to improve performance. Evaluation practices such as cross validation and using diverse performance metrics help in assessing how well the model generalizes. Continuous learning approaches, where models are updated with new data regularly, can also aid in maintaining relevance and accuracy over time. By addressing these factors, it is possible to develop deep learning models for wind energy forecasting that are both accurate and resilient when applied to new scenarios

g) Addressing long-term predictions in wind energy forecasting involves capturing and modelling dependencies over extended periods, which is crucial for effective planning and operation of wind farms. Deep learning models can leverage RNNs, particularly LSTM networks or Gated Recurrent Units (GRUs), to maintain and utilize temporal information over long sequences. These models are designed to handle the vanishing gradient problem, allowing them to remember long-term dependencies and trends in wind data. Additionally, temporal convolutional networks (TCNs) offer another approach by using dilated convolutions to capture long-range temporal dependencies more efficiently. Both approaches help improve forecast accuracy for longer time horizons, but the challenge remains in effectively managing and utilizing large amounts of historical data to avoid overfitting and ensure generalizability.

On the spatial side, wind energy prediction requires modelling spatial correlations between different measurement locations to capture how wind patterns vary across a region. CNNs can be employed to analyse spatial patterns in wind data, especially when the data is represented in a grid-like format, such as from satellite imagery or weather models. By applying convolutional layers, CNNs can extract local features and understand spatial relationships. To further enhance spatial modelling, hybrid models combining CNNs with RNNs or attention mechanisms can be used to integrate both spatial and temporal dimensions. Additionally, graph-based models, such as Graph Convolutional Networks (GCNs), can model complex spatial dependencies by representing measurement locations as nodes in a graph and learning relationships between them. Effectively accounting for these spatial correlations allows for more accurate predictions across different locations and can significantly improve the reliability of forecasts by considering the interconnected nature of wind patterns.

2.12 Research contribution.

The future gap having number "c" under the section "Finding and GAP (2.10)" focuses on enhance parameter selection, model evaluation, and data preparation in deep learning models for wind energy forecasting—a topic that has received little attention. Although these components are acknowledged, a critical gap remains unfilled: there has been no thorough investigation to address these issues. It suggests future research paths centred on developing automated tools or standardized processes to improve data preparation, perform thorough model evaluations, and fine-tune parameters.

In this thesis the above gap has addressed and fills the gap by proposing a new method—the DDN model—supported by Grid Search Optimization. This approach fills the gap in the literature by combining careful hyperparameter tuning with sophisticated deep learning algorithms. This work bridges the gap between theoretical developments and real-world application of the suggested model in wind energy prediction by using the Texas Turbine dataset for evaluation.

Moreover, the systematic examination of model architecture in the paper, which includes activation functions such as ReLU, dropout regularization, and dense layers, offers a clear implementation roadmap for utilizing comparable techniques in the field of wind energy monitoring. Significant reductions in Mean Squared Error (MSE) and MAE demonstrate the model's effectiveness and potential for practical application in renewable energy systems. These improvements in forecast accuracy are particularly noteworthy. Overall, this work successfully establishes a connection between the recognized research need and its contribution, demonstrating how the suggested methodology resolves and closes that gap in the field of wind energy forecasting.

2.13 Summary

The literature digs further into the field of renewable energy forecasting, exploring complex machine learning and deep learning models. There is an obvious shift from traditional ANNs to more advanced deep neural networks (DNNs), driven by a collective desire to improve forecasting accuracy, overcome inherent challenges, and effectively address the intricate dynamics of meteorological conditions. Notably, the literature emphasizes the critical relevance of hybrid models and ensemble methodologies in achieving precision in forecasts, particularly in the context of solar and wind energy. These investigations offer light on crucial topics such as model interpretability, showing the inner workings of complicated models as well as potential dangers in data preparation methods. Throughout the studies, the significance of precise forecasting for seamless grid integration and the broader change of energy systems is emphasized. These findings add considerably to the growing landscape of renewable energy forecasting, highlighting the need for powerful artificial intelligence algorithms and ongoing research efforts to attain future advances.

To advance this discipline, the literature prudently examines research gaps, indicating areas where additional inquiry and refinement are required to accelerate the accuracy and application of renewable energy forecasting models to new heights. This thesis fills a critical vacuum in wind energy forecasting by addressing the overlooked aspects of parameter selection, model evaluation, and data preparation in deep learning. It introduces the DDN model with Grid Search Optimization, effectively merging advanced algorithms with meticulous parameter tuning. By utilizing the Texas Turbine dataset, it showcases the practical application of this model, offering a clear path for implementing similar methodologies in wind energy monitoring. The significant improvement in forecast accuracy, evidenced by reduced MSE and MAE, underscores the model's practicality in renewable energy systems. Overall, this work not only identifies the research gap but also closes it by presenting a solution that bridges theoretical advancements with real-world application in wind energy forecasting.

CHAPTER 3: Designing of DDN Model

This chapter describes the study design used to accomplish the objectives of forecasting wind energy using the deep learning DDN model, which was optimized using the Grid Search algorithm. The research design includes the "*introduction*", "*research philosophy", "aim and objectives", "research design"* and methodology for model design and evaluation, and an examination of existing wind energy forecast models.

3.1 Introduction

The increasing dependency on energy resources has resulted in a significant annual escalation in the generation of electrical power [31], [70] Each year, there is a discernible 2% rise in global energy consumption, primarily sourced from natural gas, coal, and oil. Together, these three sources constitute the primary contributors to the world's energy production portfolio [21], [26], [47] The substantial utilization of fossil fuels considerably contributes to the emission of anthropogenic Greenhouse Gases (GHGs), consequently precipitating disturbances in the global climate. These disruptions manifest in diverse climatic phenomena, such as heightened occurrences of heavy precipitation and prolonged droughts [23], [71]. The consequential impact on climate patterns underscores the urgency for strategic interventions to curtail the deleterious consequences associated with the widespread consumption of fossil fuels [35], [72]. In the absence of restrictions on fossil fuel consumption, a notable projection anticipates a 30% surge in greenhouse gas (GHG) emissions over the next two decades [35], [47]. The utilization of traditional fossil fuels has resulted in pronounced environmental contamination, manifesting critical challenges such as global warming and air pollution [7], [58]. These emissions significantly contribute to the phenomenon of global warming and consequential shifts in climate patterns [15], [59]. Future energy consumption is expected to shift from mineral-based resources to sustainable alternatives as the environment continues to degrade and fossil fuel stocks are consumed [43], [59]. Due to its essential role in environmental protection, the growing need for eco-friendly energy has become a major global problem. Utilizing renewable energy (RE) sources like solar, wind, and biomass energy emerges as the optimal approach to address the challenges [22]. Wind energy, derived from wind turbines, stands as a renewable and eco-friendly power solution. Continuous technological advancements and innovative business models are propelling substantial growth in the wind power industry, resulting in a significant increase in its installed capacity. Amidst rapid socio-economic development, there is a notable surge in the demand for energy to fulfil the daily requirements and activities of society [14], [15]. Wind power is fundamentally about converting the energy present in moving air into electricity. However, the kinetic energy of the air that reaches a wind farm is influenced by various factors, including wind speed, wind direction, atmospheric pressure, and air temperature [73].

In the context of a wind farm dedicated to energy production, even a minor change of 1 meter per second in wind speed can lead to significant fluctuations in power output. This phenomenon arises due to the non-linear relationship between wind speed and the power generated [74]. An illustrative survey involving 19 companies highlights the substantial impact of a modest 1% improvement in minimizing prediction errors, potentially resulting in the preservation of up to 10,000 megawatts of electricity. This underscores the substantial potential of an efficient REPP model, with the capacity to yield considerable annual savings, estimated at around $1.6 million [5]. Timely wind energy forecasting is critical due to the nonlinear relationship between wind speed and power generation. However, the complexity and uncertainty of natural wind factors present challenges, necessitating effective forecasting methods [14], [44], [45].

This chapter contains on methodology of the deep learning approach to predict energy production from wind turbines. Further "*Grid search algorithm*" is used to optimize the hyperparameters to increase the precision and accuracy of the energy prediction from the wind turbines.

3.2 Research Philosophy

This study's research methodology is grounded in pragmatism and emphasizes a practical approach to improving the accuracy of wind energy forecasts. As the underlying methodology, pragmatism allows the integration of theoretical knowledge from the body of literature with practical applications in real-world situations. This pragmatic approach guarantees a well-balanced synthesis of theoretical knowledge and practical implications, closely coordinating the study with the demands and obstacles present in the wind energy area. This study attempts to close the knowledge gap between theoretical developments and real-world applications by using a pragmatic approach and providing insightful information that can be used immediately to improve wind energy forecast models.

3.3 Research Design

3.3.1 Research Approach

The proposed DDN model's performance is evaluated using a quantitative research technique that stresses the use of numerical data and statistical analysis. In the context of wind energy generation forecast, a quantitative approach is ideal for evaluating the model's effectiveness using rigorous numerical measurements and statistical analysis. The quantitative research technique entails the collecting and analysis of numerical data, with a particular emphasis on performance indicators such as Mean Squared Error (MSE) and MAE. These metrics quantify the model's prediction accuracy by calculating the squared and absolute differences between anticipated and observed values.

3.3.2 Research Strategy

The research strategy combines literature review, data collecting, model creation, and model optimization. The study begins with a thorough examination of existing wind energy prediction models, laying the groundwork for the construction of the DDN model. The Grid Search technique is then used to refine the model parameters, hence improving its predictive powers.

3.3.3 Methods and technique

3.3.3.1 Data collection

To train this model "*Texas turbine dataset"* in CSV format has used. The dataset contains on the four variables including "*wind speed"*, "*wind direction*", "*wind pressure*", and "*wind temperature*". as visualized Figure 3.1.

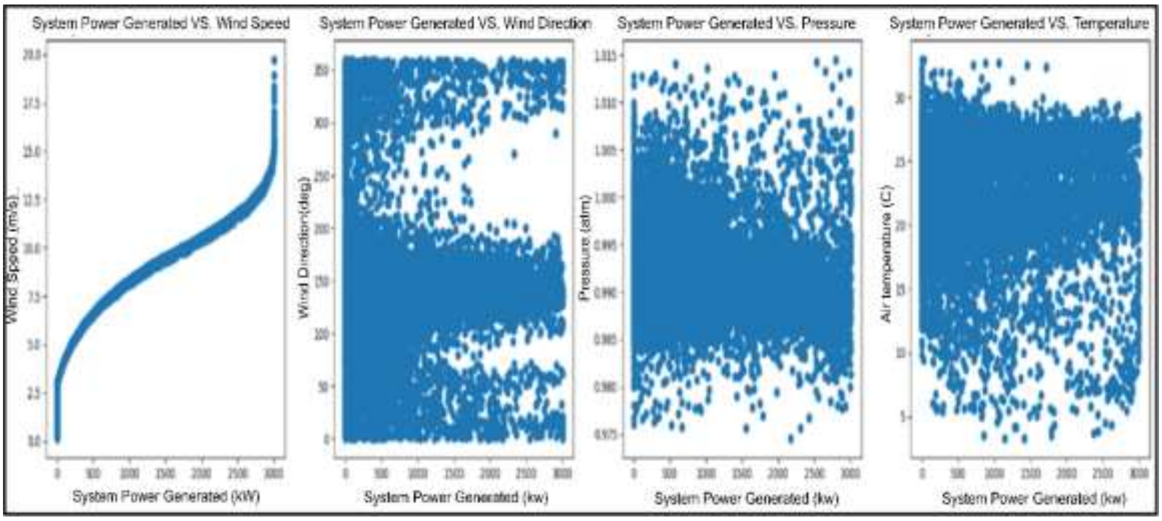

Figure 3.1: Dataset variables

The different variables of the dataset are also visualized as given in Figure 3.2.

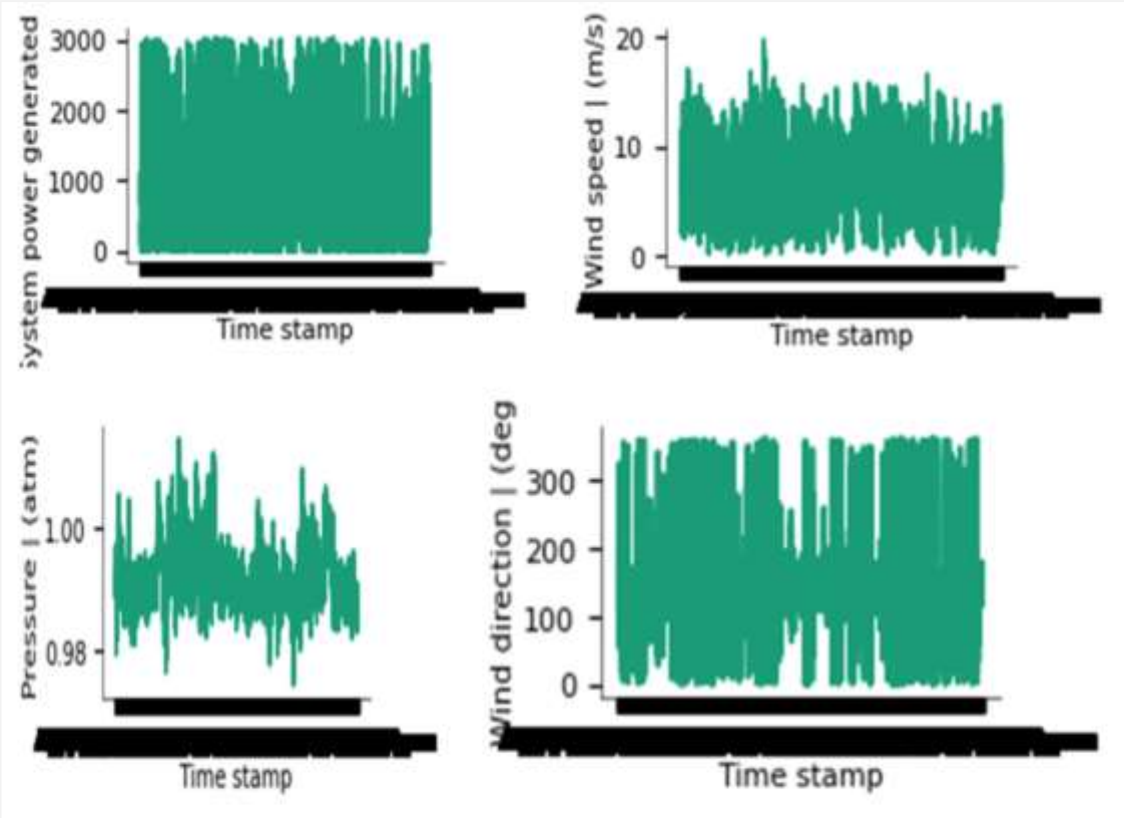

Figure 3.2: Time stamp of dataset variables

3.3.3.2 Data preprocessing

The dataset is meticulously divided into three distinct subsets, each serving a crucial role in the development and evaluation of the model. The training set, constituting 80% of the data with 7008 rows and 6 columns, acts as the primary source for model learning, allowing it to discern patterns and relationships within the dataset. Simultaneously, the testing subset, comprising 10% of the data (876 rows x 6 columns), remains untouched during the model's training phase and serves as a critical benchmark for evaluating the model's performance on new, unseen data. Complementing this, the validation set, also 10% of the data (876 rows x 6 columns), provides an additional layer of scrutiny. Its purpose is to fine-tune model parameters, ensuring enhanced robustness and reliability. This meticulous preprocessing, involving strategic allocation into training, testing, and validation sets, establishes a robust foundation, fostering accurate insights and reliable model training outcomes.

3.3.3.3 Model parameters

In table 1, the layer specification of the model and the other critical parameters used to train to train the model and the total Total params are given in table 3.1.

Table 3.1: Model parameters

<table>
<tr><td>Parameter</td><td>Neurons</td><td>Dropout Rate</td></tr>
<tr><td>Hidden 1</td><td>512</td><td rowspan="8">0.4</td></tr>
<tr><td>Hidden 2</td><td>256</td></tr>
<tr><td>Hidden 3</td><td>128</td></tr>
<tr><td>Hidden 4</td><td>64</td></tr>
<tr><td>Hidden 5</td><td>32</td></tr>
<tr><td>Hidden 6</td><td>16</td></tr>
<tr><td>Hidden 7</td><td>8</td></tr>
<tr><td>Output</td><td>1</td></tr>
<tr><td colspan="2">loss function</td><td>MSE</td></tr>
<tr><td colspan="2">Activation function</td><td>ReLU</td></tr>
<tr><td colspan="2">Optimizer</td><td>Adam</td></tr>
<tr><td colspan="2">Learning rate</td><td>0.1</td></tr>
<tr><td colspan="2">Evaluation metrics</td><td>MSE and MAE</td></tr>
<tr><td colspan="2">Epochs</td><td>30</td></tr>
<tr><td colspan="2">Total params</td><td>177793</td></tr>
<tr><td colspan="2">Trainable params</td><td>177793</td></tr>
</table>

3.3.3.4 Model design

The dataset "*Texas turbine dataset"* is for is used for training, contains on various variables Wind speed, Wind direction, Pressure, Air temperature and divided inti three parts. The training part of the dataset is used as input for the proposed DDN model. The DDN model is structured with eight densely connected layers, featuring a descending hierarchy of neurons: 512, 256, 128, 64, 32, 16, 8, and 1. The activation function employed across these layers is Rectified Linear Unit (ReLU), except for the output layer which remains inactivated, facilitating direct regression. Dropout regularization is strategically incorporated after each dense layer with a dropout rate of 0.4, randomly deactivating 40% of neurons during training to forestall overfitting and enhance the model's generalization capabilities. Training the model involves utilizing the 'mean squared error' (MSE) loss function, focusing on minimizing the average squared differences between predicted and actual values. This approach refines the model's weights and biases during training to enhance its predictive accuracy. Model performance is evaluated using both MSE and MAE. The detailed diagram in Figure 3-3 visually represents the architecture of the DDN model, elucidating the connectivity and flow of information through the network. Overall, the DDN model is meticulously crafted to capture intricate data relationships, mitigate overfitting through dropout regularization, and provide reliable predictions for continuous output in the context of wind energy generation. The proposed model is given in Figure 3.3.

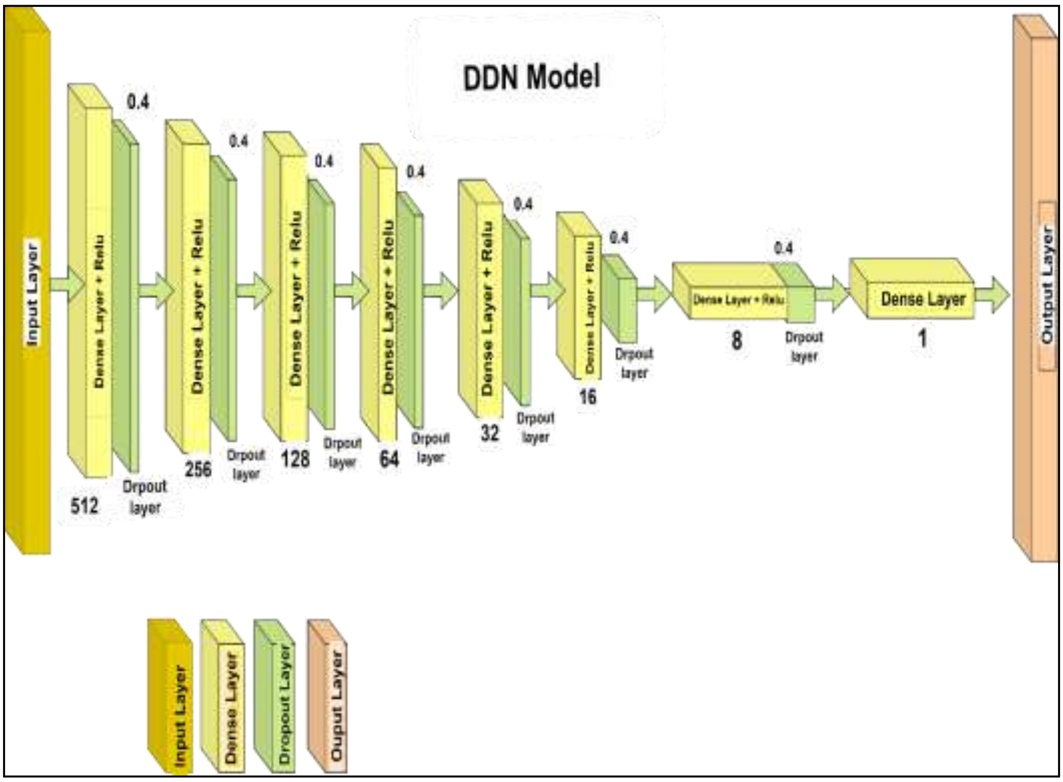

Figure 3.2: Model architecture

3.3.3.5 Dense Layers

In the context of the 'Texas Turbine' dataset, the architecture of the dense layer in a neural network involves the manipulation of input features to produce meaningful predictions. The input vector (denoted as 'x') encapsulates the various parameters such as wind speed, wind direction, pressure, and air temperature. The weight matrix ('W') represents the learned weights assigned to each feature during the training process, influencing their significance in the prediction. The bias term ('b') is an adjustable parameter introduced to fine-tune the weighted sum of inputs. The core transformation occurs through the application of a Rectified Linear Unit (ReLU) activation function to the sum of the weighted inputs and bias [6], [50].

$$Y= \sigma (W \cdot X +b) \qquad (1)$$

where σ denotes the ReLU activation function. This process introduces non-linearity, enabling the neural network to capture intricate patterns and relationships within the data. The output ('Y') of the dense layer is fundamental for subsequent layers in the network and plays a crucial role in predicting the system power generated in the case of wind energy forecasting.

3.3.3.6 Dropout layer

Where dropout Layer is a regularization method employed in neural networks to avoid overfitting. When a model develops strong performance on the training set but unable to generalize to brand-new, untried data, overfitting takes place. Dropout is intended to address this problem by randomly "dropping out" a part of neurons throughout each training session [5], [46]. Assume that x is the neuron's input, ware its weights, b is its bias, and dare its dropout mask (0s and 1s that indicate whether a neuron is dropped out or not)[31], [33], [43]. After employing dropout, the neuron's response y is given in equation (2)

$$y=d\cdot(w\cdot x+b) \qquad (2)$$

Were, d is a random binary mask, with entries that are each separately sampled from a Bernoulli distribution with a parameter p that represents the dropout rate, in this case the p value is 0.4. The dropout layer will drop 40% of the neurons randomely during each training cycle, preventing overfitting [21], [33], [45], [46].

3.4 The model evaluation

3.4.1 Mean Absolute Error

The MAE is a statistic for assessing the performance of a regression model. It calculates the average absolute difference between the expected and actual values [54]. The mathematical definition is as follows.

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n} |\,\text{ytrue}_{[i]}\text{-ypred}_{[i]}| \qquad (3)$$

Where n is number of datapoints

$\text{ytrue}_{[i]}$ are the ground truth, and the $[i]$ indicates the datapoints.

$\text{ypred}_{[i]}$|are the predicted points and the $[i]$represents the datapoints.

MAE is the MAE between expected and actual values. It is simple to evaluate because it provides the average amount of error without considering their direction (overestimation or underestimation). Lower MAE values indicate improved model performance. MAE is one of the metrics used to evaluate the proposed model. During training, the model seeks to reduce the MAE loss to enhance its forecast accuracy. Following training, the MAE on a separate validation or test dataset indicates how effectively the model generalizes to new, unseen data [19], [43].

3.4.2 Mean Squared Error (MSE)

The MSE is a statistic that assesses the performance of a regression model by calculating the average squared difference between predicted and ground truth values [48].

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}(\text{ytrue}_{[i]}\text{-ypred}_{[i]})^2 \qquad (4)$$

Where n is number of datapoints

$\text{ytrue}_{[i]}$ are the actual values, and the $[i]$ specifies the datapoints.

$\text{ypred}_{[i]}|$ are the predicted points and the $[i]$signifies the datapoints.

The MSE computes the squared difference between each predicted value and the associated actual value. It then calculates the average of the squared differences across all data points. Squaring the differences has two primary functions: it penalizes greater errors more severely than smaller errors, and it assures that all differences are positive. A lower MSE indicates greater model performance, projected values are closer to actual values. MSE is one of the metrics utilized in the research to assess the performance of the wind energy prediction model[28], [44].

3.4.3 The Model Limitation

The performance of the DDN model was assessed using two key metrics in regression tasks: Mean Squared Error (MSE) and MAE. MSE, defined as the average of squared differences between predicted and actual values, and MAE, which represents the average of absolute differences, were used as quantitative indications of the model's accuracy. The use of these criteria was intended to evaluate how effectively the DDN model reflected the complicated patterns in the Texas turbine dataset. The obtained results were judged promising, with a low MSE and MAE, indicating minor differences between anticipated and ground truth values. However, acknowledging the importance of complete model evaluation, the statement emphasizes the need for additional research. This includes testing the model on diverse datasets beyond the Texas turbine data and exploring additional evaluation metrics to provide a more nuanced understanding of the model's strengths and weaknesses. The acknowledgment of "promising results" signifies an initial positive outcome while emphasizing the ongoing need for rigorous testing and validation to ensure the model's robustness across various wind energy prediction scenarios.

3.4.4 Model evaluation before optimization.

Initially, the dataset is preprocessed by scaling the features using a MinMaxScaler. A neural network model is then specified as a function, which allows for greater flexibility in altering hyperparameters. The architecture incorporates numerous thick layers with set activation functions and dropout rates to reduce overfitting.

The KerasRegressor wrapper is used to incorporate the neural network model into the scikit-learn framework, making it compatible with GridSearchCV. The hyperparameter grid is defined to include learning rates, dropout rates, batch sizes, and epochs. The grid search is then performed using three-fold cross-validation to assess the model's performance on various subsets of the training data.

Following the grid search, the best hyperparameters and their mean squared error (MSE) are extracted. The determined optimal hyperparameters provide insight into the setup that minimizes prediction errors. This information is critical to improving the model's accuracy and generalizability. The final output shows the best hyperparameters and their related MSE, giving a full overview of the grid search results and enabling further development of the neural network model for better regression performance.

3.5 Summary

The chapter describes a detailed study design for forecasting wind energy using the DDN model optimized with the Grid Search algorithm. The introduction discusses the global energy landscape, highlighting the importance of sustainable options owing to environmental concerns. Wind energy emerges as a possible alternative, but good forecasting is critical due to the nonlinear relationship between wind speed and power generation.

The research philosophy takes a pragmatic approach, combining theoretical knowledge and real-world applications. The goal is to anticipate wind energy using the Texas Turbine dataset, deep learning, and Grid Search. The objectives include a literature review, model development, optimization, performance evaluation, visualization, and comparison to current models.

The research strategy takes a quantitative approach, focusing on numerical data and statistical analysis. A thorough literature review preceded the development and optimization of the DDN model. The model's architecture, parameters, and design are thoroughly detailed, including dropout layers for regularization. Mean Squared Error (MSE) and MAE are two common evaluation measures.

Limitations acknowledge the need for more comprehensive dataset testing and evaluation metrics. Prior to optimization, the model is evaluated by preprocessing, defining the neural network, utilizing KerasRegressor with GridSearchCV, and extracting the ideal hyperparameters. The summary presents an organized and detailed framework for improving wind energy forecasts using deep learning and optimization techniques.

CHAPTER 4: Results and Discussions

This chapter explores the complexities of wind energy forecasting, which is crucial for advancing sustainable energy solutions. The sections that provide a comprehensive overview of the various elements that contribute to the development and evaluation of a sophisticated forecasting model. From the initial introduction highlighting the global energy landscape and the growing importance of wind energy, progressing to a detailed evaluation of the model's performance metrics, key parameters and dataset characteristics are meticulously outlined, emphasizing the importance of data partitioning and preprocessing. The neural network architecture is also explored, including its design and the rationale behind the choice of specific parameters and techniques. The culmination of these efforts is the DDN model, an advanced deep learning approach aimed at enhancing the accuracy and efficiency of wind energy forecasting. This framework not only underscores the potential of deep learning in renewable energy applications but also paves the way for more reliable and precise energy management strategies.

4.1 Introduction

In recent years, the global energy landscape has undergone a significant transformation driven by technological advancements and growing environmental concerns [18]. The escalating demand for electricity, coupled with the urgent need to mitigate the adverse effects of fossil fuel consumption, has propelled the exploration of alternative energy sources [26]. Among these, wind energy has emerged as a promising solution due to its renewable nature and minimal environmental impact [24]. As a result, the wind power industry has witnessed substantial growth, contributing significantly to the global energy mix [32]. In 2020, the installed capacity of wind power worldwide reached an impressive 93 GW, marking a substantial increase of 52.96% compared to the previous year [23]. This growth underscores the pivotal role of wind energy in addressing energy needs and sustainability challenges. However, despite its potential, the efficient harnessing of wind energy poses challenges, particularly in accurately forecasting energy production [7]. The nonlinear relationship between wind speed and power generation, compounded by the complexity and uncertainty of natural wind factors, necessitates sophisticated forecasting methods [20]. To address these challenges, this study introduces a novel deep learning-based approach called DDN. Leveraging advancements in deep learning and optimization techniques, the DDN model aims to enhance the efficiency and accuracy of wind energy forecasting [46]. By integrating grid search optimization, the model systematically identifies optimal hyperparameters, thereby improving predictive performance [22]. The significance of this research lies in its potential to revolutionize wind energy forecasting by providing a reliable and precise tool for energy producers and policymakers [19]. By accurately predicting energy production from wind turbines, the DDN model can facilitate more efficient energy management and distribution, contributing to the transition towards a sustainable energy future [21].

4.2 Dataset

In the context of wind energy prediction, the dataset plays a crucial role as it serves as the foundation for training and evaluating forecasting models. Here's an elaboration on the dataset specifically tailored for wind energy prediction. The dataset utilized for wind energy prediction typically comprises various meteorological and environmental variables collected over a period. These variables include.

Wind Speed: Wind speed is one of the primary factors influencing the generation of wind energy. It represents the velocity of the wind, measured typically in meters per second (m/s) or kilometres per hour (km/h) [75].

Wind Direction: Wind direction indicates the compass direction from which the wind is blowing. It is usually measured in degrees, with values ranging from 0° (north) to 360° (north again) [29].

Air Temperature: Air temperature refers to the degree of hotness or coldness of the air. It is measured typically in Celsius (°C) or Fahrenheit (°F) and can impact wind energy generation by influencing air density and turbine performance.

Pressure: Atmospheric pressure, often measured in millibars (mb) or hectopascals (hPa), represents the force exerted by the weight of the air above a given point. Changes in atmospheric pressure can affect wind patterns and thus wind energy generation [59]. The given dataset is visualised as given in Figure 4.1.

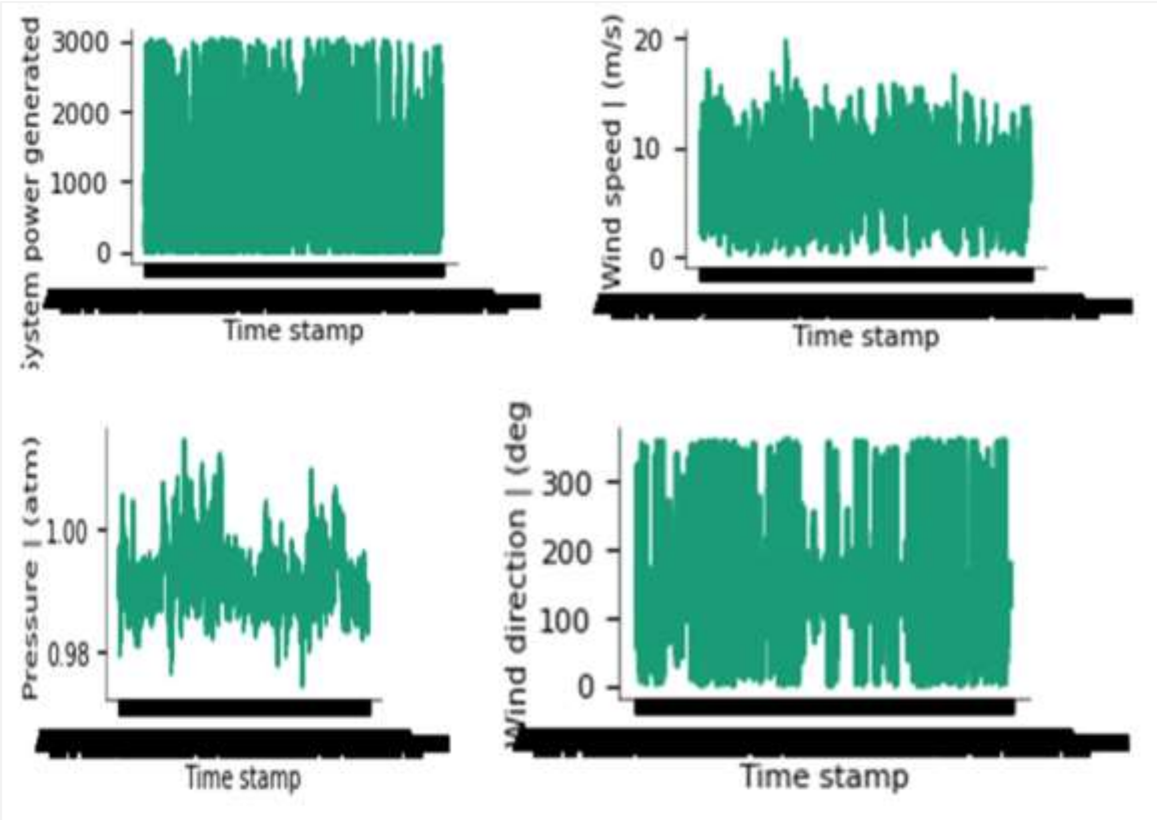

Figure 4.1: Texas Turbine dataset

The dataset is carefully partitioned into three distinct subsets, each playing a vital role in the model development and assessment process. The training set, comprising 80% of the data with dimensions of 7008 rows and 6 columns, serves as the primary source for the model to learn intricate patterns and correlations within the dataset. Meanwhile, the testing subset, representing 10% of the data (876 rows x 6 columns), remains segregated during the model's training phase and serves as a pivotal benchmark for evaluating its performance on novel, unseen data instances. Additionally, the validation set, also consisting of 10% of the data (876 rows x 6 columns), serves to fine-tune model parameters, ensuring heightened robustness and dependability. This meticulous pre-processing, involving deliberate allocation into training, testing, and validation sets, establishes a solid groundwork, fostering precise insights and trustworthy model training outcomes.

4.3 Model Architecture

The proposed DDN model is structured with eight dense layers, each utilizing the Rectified Linear Unit (ReLU) activation function except for the output layer, which remains un activated for direct regression. To enhance generalization and prevent overfitting, dropout regularization is incorporated after each dense layer, with a dropout rate set at 0.4, randomly deactivating 40% of neurons during training sessions.

Throughout the training process, the DDN model undergoes 50 epochs with a batch size of 128 and a validation split of 0.1. The learning rate is set at 0.001, and the Adam optimizer is utilized along with an early call-back mechanism to optimize model performance. The model employs both Mean Squared Error (MSE) and MAE loss functions to measure the discrepancy between predicted and actual values. The layer architecture along with number of neurons is given in Figure 4.2.

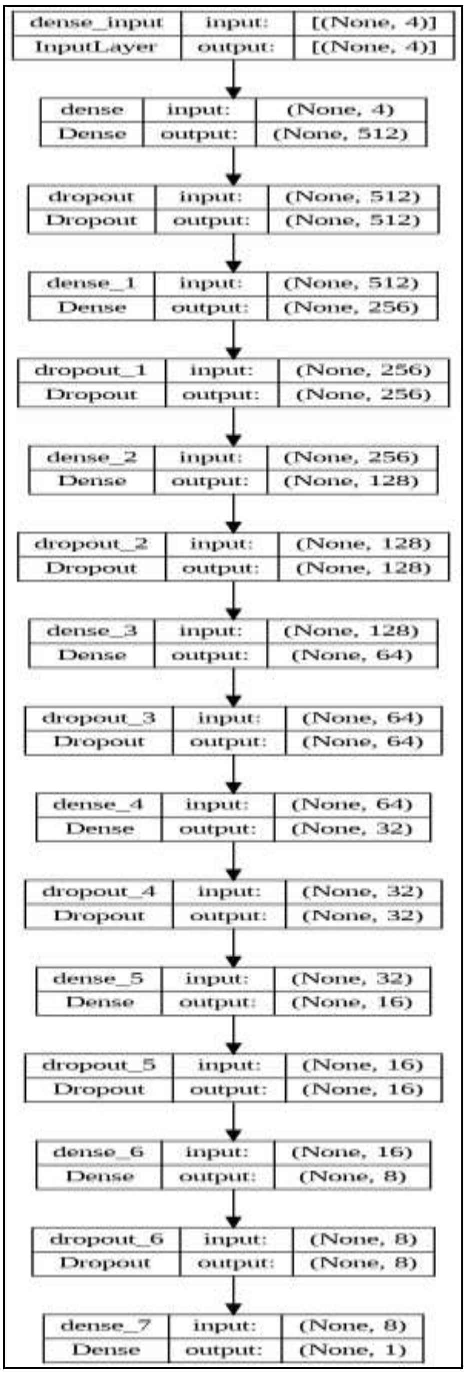

Figure 4.2: Proposed Model DDN architecture.

In Figure 4.2, a neural network architecture has shown which begins with an input layer that accepts data with 4 features. Following this, the network comprises a series of dense (fully connected) layers interspersed with dropout layers for regularization. The first dense layer transforms the 4 input features into 512 neurons, which is then followed by a dropout layer to prevent overfitting by randomly setting a fraction of input units to zero during training. This pattern continues with subsequent dense layers progressively reducing the number of neurons from 512 to 256, then 128, 64, 32, 16, and finally 8, each followed by a corresponding dropout layer. The final dense layer reduces the number of neurons from 8 to 1, producing the network's output. This configuration of dense and dropout layers aims to build a robust model that can generalize well to new data, making it suitable for tasks such as regression or binary classification.

4.4 Results and Discussion

The training and validation curves depicted in Figure 4.3 provide crucial insights into the performance and generalization capability of the DDN model.

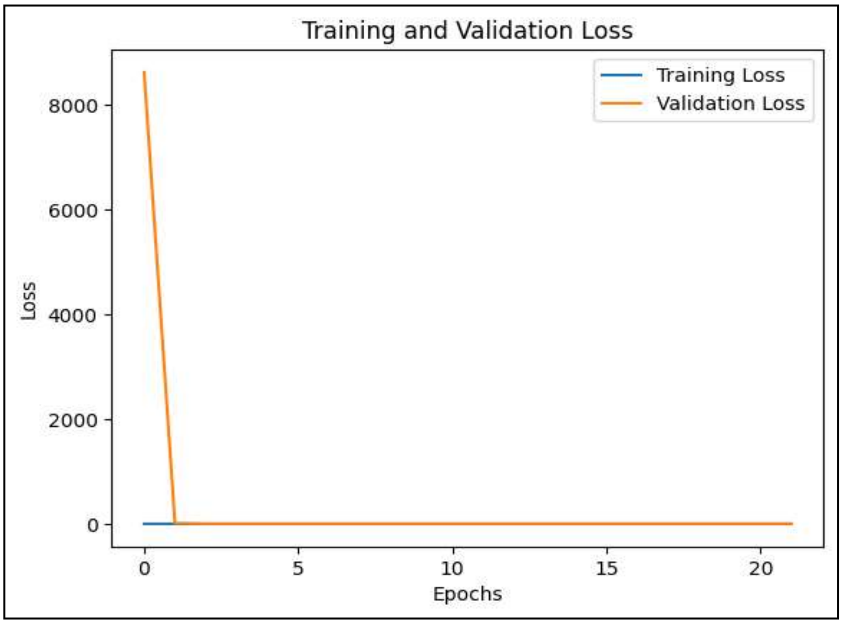

Figure 4.3: Training and validation curve

Initially, during the early epochs, both the training and validation losses decrease steadily, indicating that the model is effectively learning from the training data and improving its predictive performance. This phase reflects the model's ability to capture underlying patterns and relationships present in the training dataset. As training progresses, the training loss continues to decrease gradually, indicating that the model is refining its parameters to minimize errors on the training data. However, it is essential to monitor the validation loss concurrently. If the validation loss begins to increase while the training loss decreases, it may suggest that the model is overfitting the training data, capturing noise rather than genuine patterns.

In the case of the DDN model, the convergence of training and validation losses signifies effective generalization. A steady decrease in both losses without significant divergence suggests that the model is learning meaningful representations from the data while maintaining its ability to generalize well to unseen examples. Moreover, if there is a substantial gap between the training and validation losses, it may indicate that the model is overfitting, as it performs significantly better on the training data compared to the validation data. Conversely, if the validation loss is consistently lower than the training loss, it may suggest that the model is underfitting, failing to capture essential patterns in the data. Overall, a close examination of the training and validation curves allows for the assessment of model performance, ensuring that it achieves the right balance between learning from the training data and generalizing well to unseen examples. In the case of the DDN model, the convergence of training and validation losses indicates its effectiveness in learning from the data while maintaining robust generalization capabilities. Figure 4.4 reflects the training MSE and Training MAE along with the Training loss and validation loss.

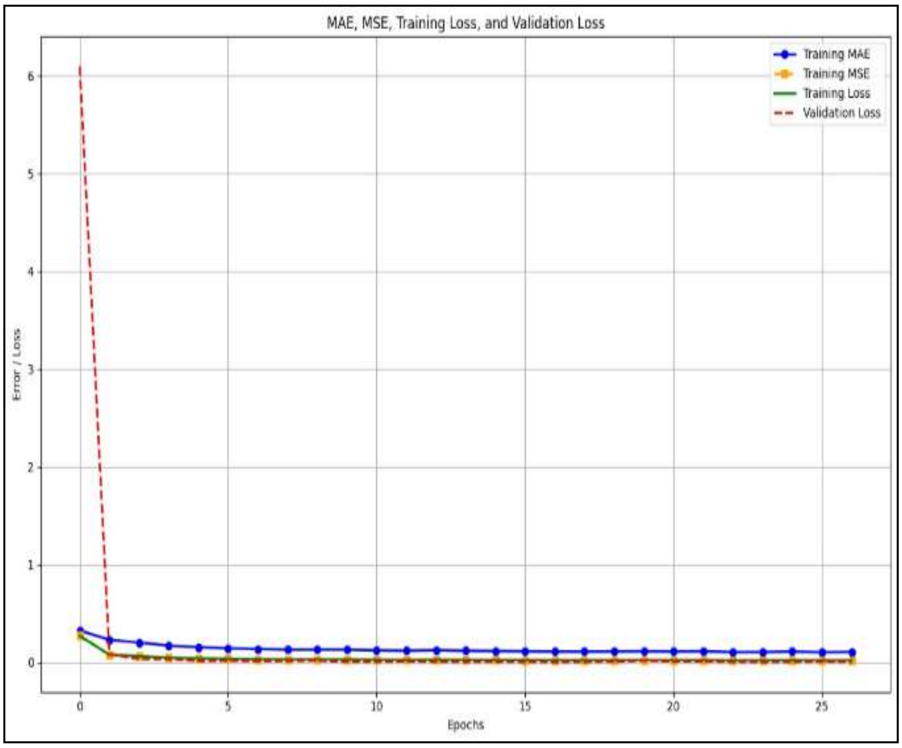

Figure 4.4: Training MAE, MSE, training and validation loss.

Figure 4.4 provides valuable insights into the model's learning process and its ability to generalize to new, unseen data. The convergence of the training and testing curves indicates that the model is effectively learning underlying patterns present in the training data and can apply them to unseen examples. This convergence suggests that the model's performance on the testing data is consistent with its performance on the training data, indicating robust learning and generalization capabilities. Moreover, Figure 8 offers a comprehensive overview of the model's performance metrics, including MAE, MSE, training loss, and validation loss, across the training epochs. These metrics provide a detailed understanding of how the model's performance evolves over the course of training. The MAE and MSE metrics quantify the model's accuracy by measuring the average absolute difference and the average squared difference, respectively, between the predicted and actual values. A decreasing trend in both MAE and MSE indicates that the model is improving its predictive accuracy as training progresses. Similarly, the training and validation loss curves depict the evolution of the model's performance in terms of minimizing errors during training. A decreasing trend in both training and validation loss indicates that the model is effectively learning from the data and minimizing errors. The convergence of these curves suggests that the model is not overfitting or underfitting the data but rather achieving a balance between learning from the training data and generalizing well to unseen examples.

Grid Search Cross-Validation is a systematic approach used to find the best combination of hyperparameters for a machine learning model. In the context of the proposed DDN model, Grid Search Cross-Validation is employed to identify the hyperparameter settings that minimize both Mean Squared Error (MSE) and MAE on the training data. During the Grid Search process, various combinations of hyperparameters are explored systematically. These hyperparameters may include parameters such as learning rate, dropout rate, number of neurons in each layer, and so on. For each combination of hyperparameters, the model is trained and evaluated using cross-validation, where the dataset is divided into multiple subsets, and the model is trained on different subsets and validated on the remaining subset. This helps to ensure that the model's performance is robust and not dependent on a particular subset of data. The table indicate the improvement in term of percentage.

Table 4.1: DDN before and after grid search

Metric	DDN before Grid search	DDN after Grid search	Percentage (%) improved
MSE	0.0785	0.0047	94.013
MAE	0.2376	0.0548	76.8474

In

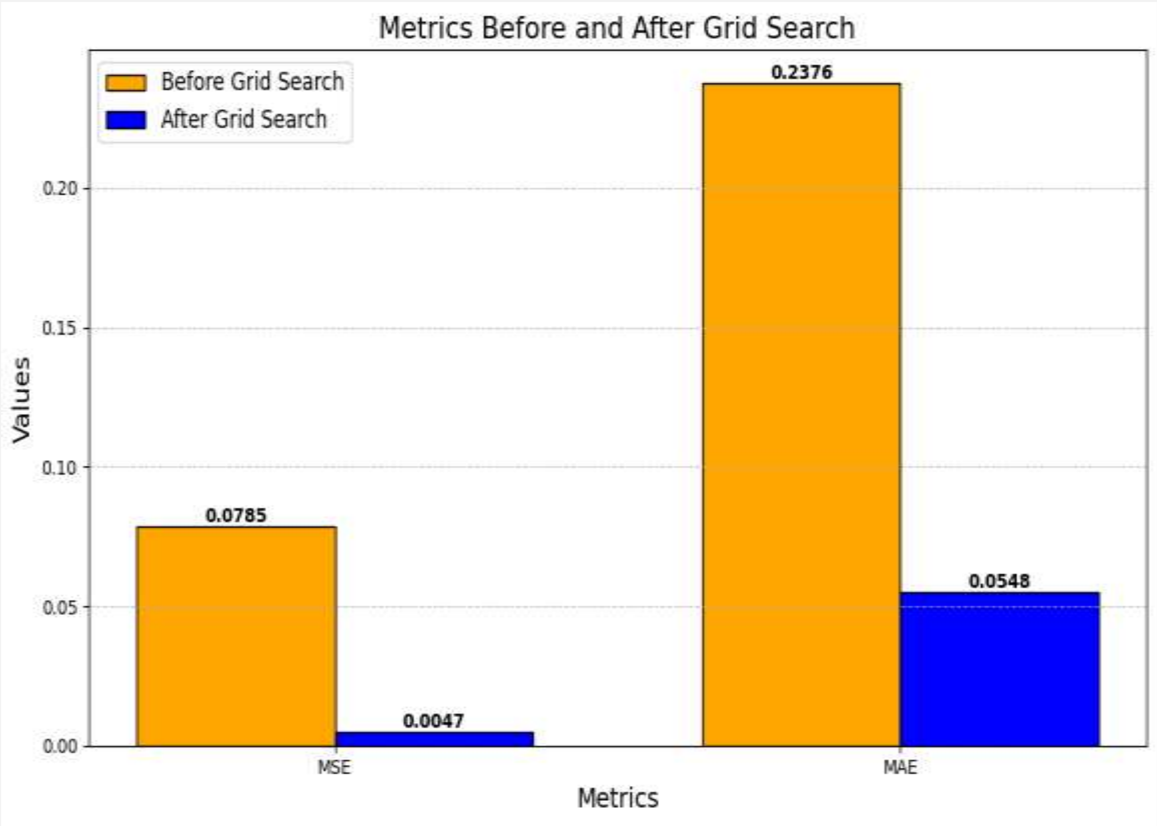

Figure 4.5, the graph provides a detailed visual depiction of the MAE and MSE values, offering insights into the model's performance both before and after optimization. By comparing the two sets of metrics displayed in the graph, viewers can easily discern the impact of optimization on the model's accuracy. The before optimization values serve as a baseline, indicating the initial performance levels, while the after-optimization values demonstrate the enhancements achieved through the refinement process. This comparison aids in understanding the effectiveness of the optimization techniques employed and highlights the tangible improvements in prediction accuracy.

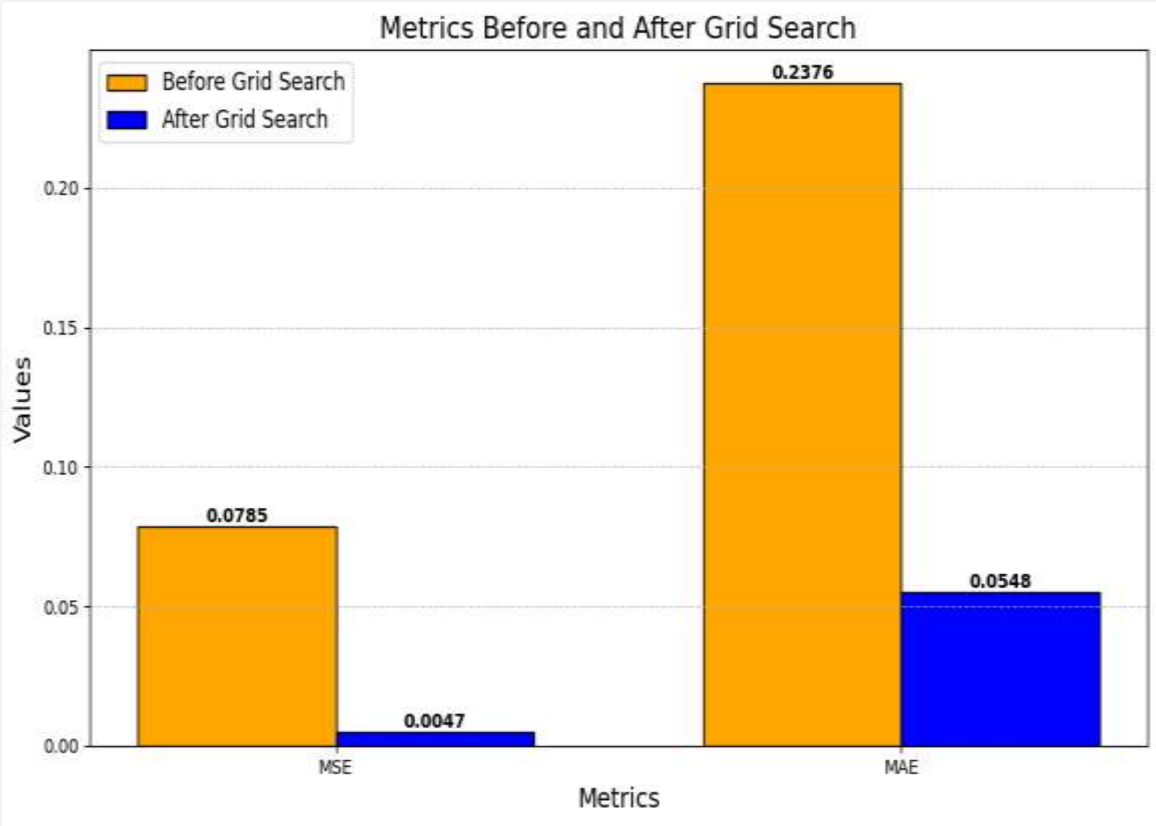

Figure 4.5: DDN model before and after optimization.

In Figure 4.6, the scatter plot vividly illustrates the relationship between the predicted values produced by the Denoising Deep Network (DDN) and the ground truth values extracted from the Texas Turbine dataset. Each data point on the plot symbolizes a specific data sample, showcasing the model's performance across the entire dataset. The red dashed line, representing the ideal prediction line, serves as a reference point for perfect alignment between predicted and actual values. By examining the deviations of data points from this ideal line, a nuanced understanding of the model's accuracy and precision in predicting wind energy output is gained, with the black line indicating the predicted values. This visual comparison provides valuable insights into the model's ability to generalize and make reliable predictions on unseen data, thereby aiding in the assessment of its overall efficacy and performance.

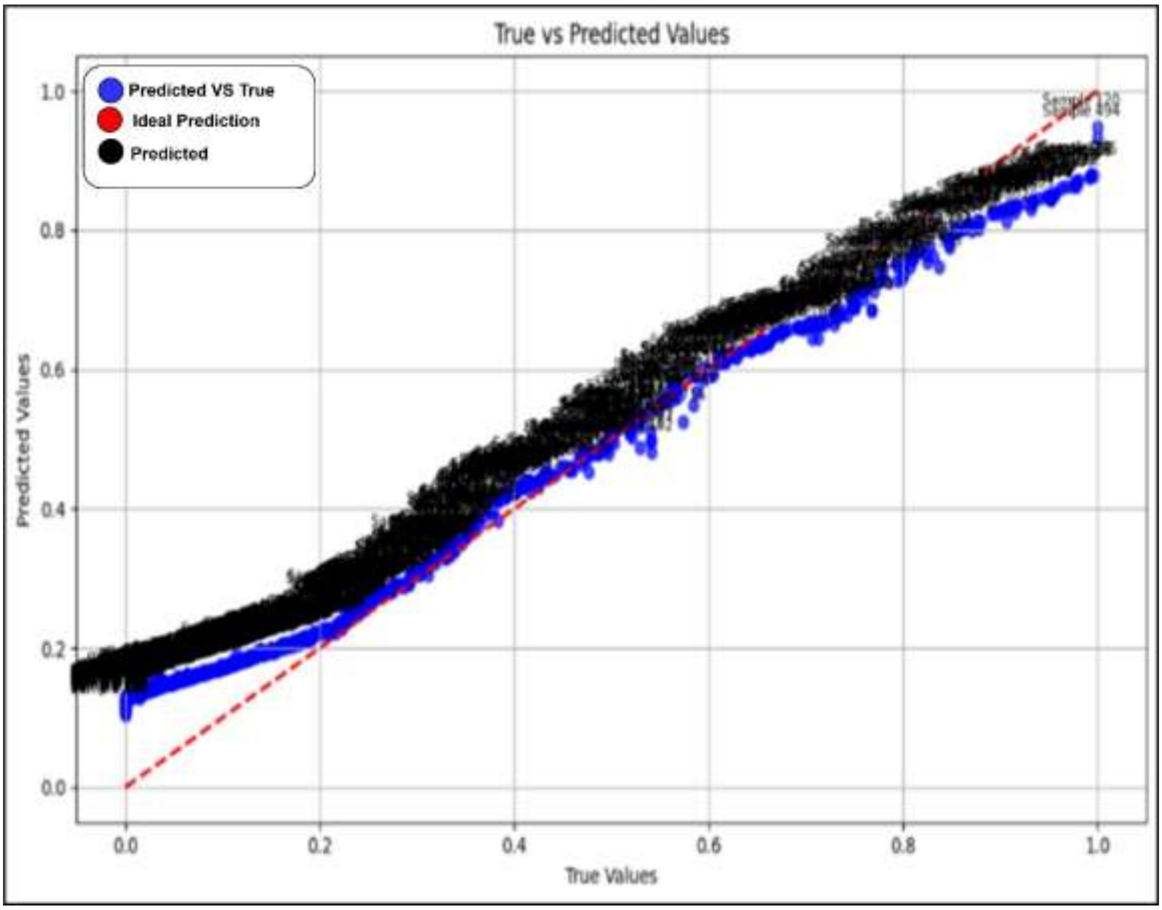

Figure 4.6: Predicted Vs True Values

In Figure, residual plots are utilized to evaluate the performance of a regression model by visually depicting the discrepancies between the predicted values generated by the model and the actual observed values. Each data point on the plot represents the difference, or residual, between the predicted and observed values. The red dashed line at zero serves as a reference point, indicating perfect alignment between predicted and observed values. Deviations above or below this line signify overestimation or underestimation, respectively, by the model. By analysing the distribution of residuals across the range of observed values, patterns such as heteroscedasticity, non-linearity, and the presence of outliers can be identified. These insights are crucial for assessing the reliability of the model and making any necessary adjustments to improve its predictive accuracy.

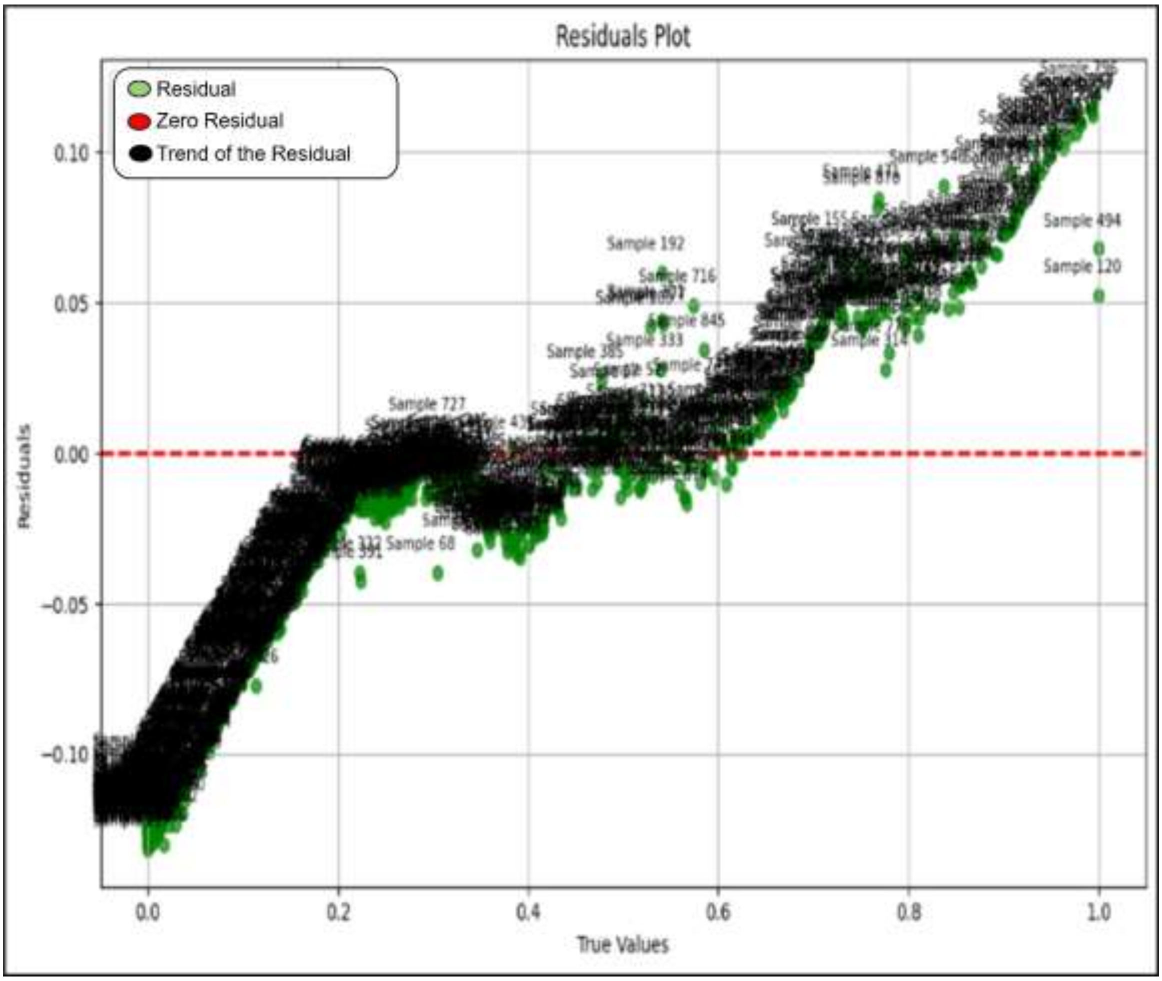

Figure 4.7: Residual plot of DDN model.

4.5 Summary

In this study, the development of a Deep Dense Network (DDN) model designed is presented to enhance the efficiency of wind energy forecasting. Utilizing a combination of dense and dropout layers, a Grid Search Optimization is employed to fine-tune the model's parameters. The analysis is based on the Texas turbine dataset, which includes four key variables.

This research builds upon prior literature, which suggests that simpler models with dense layers and dropout regularization are more practical than complex, computationally intensive models. The findings confirm that this streamlined approach provides comparable results while significantly reducing computational overhead.

Grid Search Optimization allowed us to identify optimal hyperparameters, such as learning rate, activation function, batch size, dropout rate, and number of epochs. Fine-tuning these parameters led to substantial improvements in the model’s predictive performance. Specifically, the Mean Squared Error (MSE) decreased from 0.0785 to 0.0047, representing a 94.013% improvement, while the MAE reduced from 0.2376 to 0.0548, reflecting a 76.8474% improvement. Additionally, the model's performance is compared to existing algorithms using RMSE and MAE as comparative measures.

Dense layers are crucial in neural networks for learning and representing complex data interactions. By combining linear transformations with nonlinear activation functions, these layers facilitate hierarchical feature learning and adaptive parameter adjustments. The inclusion of dropout layers helps prevent overfitting by randomly deactivating neurons during training, promoting more generalized data representations and enhancing performance on unseen data.

In comparison to more complex architectures, the DDN model demonstrates robustness and superior performance. Future research will focus on expanding the model’s depth and width using residual blocks and evaluating its effectiveness with larger datasets.

CHAPTER 5: Conclusion and Future Work

Renewables have grown to be of prime interest to the today's world because of their promising solution to the existing challenges faces by the world. Wind energy is one of the largest sources of renewable energy. Due to the variable nature of the environment, the wind energy never remains constant and keeps on changing depending on time, locations, weather, and other environmental factors. Forecasting involves the prediction of wind energy available at a certain time or within a certain period. Wind energy forecasting helps better planning and utilisation of resources. Furthermore, the forecasting provides an important insight to the economic viability of certain renewable energy project by shedding light on the available energy to be harvested in future. While conventional forecasting involves studying and predicting the climatic changes e.g. clouds, rains, wind speeds etc; however, the conventional forecasting is static and does not involve any intelligent decision making without human intervention. AI can prove to be a valuable tool for smart and continuous forecasting based on the historical data and patterns.

The project streamlines its aims and objectives with this problem and performed a research and design of dense deep neural network for forecasting purposes. The model was extensively tested with benchmark results and the performance.

5.1 Key Findings and Model Performance

The proposed DDN model, which incorporates dense layers and dropout regularization, was successfully implemented and tested using a comprehensive dataset of wind energy variables, including wind speed, wind direction, wind pressure, and wind temperature. The model's architecture comprises eight densely connected layers with neurons in a descending hierarchy (512, 256, 128, 64, 32, 16, 8, and 1) and employs the Rectified Linear Unit (ReLU) activation function, except for the output layer, which remains unactivated for direct regression. Dropout regularization with a rate of 0.4 was applied to mitigate overfitting and improve generalization. Training was conducted using the 'mean squared error' (MSE) loss function to refine the model's weights and biases. Performance metrics, including MSE and MAE, demonstrated substantial improvements due to the Grid Search Optimization. Specifically, the MSE decreased from 0.0785 to 0.0047, representing a 94.013% reduction, while the MAE improved from 0.2376 to 0.0548, reflecting a 76.8474% decrease. This indicates that the optimization process significantly enhanced the model's predictive accuracy.

5.2 Discussion of Results

Figures and graphs in the study illustrate the model's performance. Figure 4-3 shows a steady decrease in both training and validation losses, indicating effective learning from the training data and improved generalization to unseen examples. Figure 4-4 confirms the convergence of training and validation metrics, suggesting robust learning and performance consistency. Figure 4-5 provides a visual comparison of MAE and MSE values before and after optimization, highlighting the positive impact of Grid Search Cross-Validation on the model’s accuracy. The comparison underscores the enhancements achieved through the refinement process. Comparative analysis with the Texas Turbine dataset (Figure 4-6) confirms that the DDN model accurately forecasts wind energy generation. Figure 4-7 illustrates the alignment between expected and observed values, demonstrating high accuracy with minimal deviations.

5.3 Contributions and Implications

The study highlights the potential of deep learning approaches, particularly the DDN model, in enhancing wind energy forecasting. The findings suggest that DDN, with its ability to capture complex temporal patterns and dependencies, is a promising tool for accurate prediction tasks. This model offers practical applications in various fields where precise forecasting is crucial, including renewable energy management and economic viability assessment.

5.4 Future directions

Renewable energy and deep learning are rapidly evolving fields with considerable potential for further research. Despite recent advancements, several critical research gaps persist, offering numerous opportunities for exploration. Based on the current study, the following future research directions are proposed:

1. **Expansion of Dataset Size and Quality**:
   - **Enhancing Data Availability**: Deep learning models, particularly dense networks, require extensive and diverse datasets to achieve high forecasting accuracy. Future research should focus on acquiring larger datasets from various geographical regions and operational contexts to improve model performance.
   - **Standardization and Quality Assurance**: Developing techniques for standardizing and ensuring the reliability of datasets is crucial. Research

should address methods for data cleaning and consistency to enhance the robustness and generalizability of forecasting models.

2. **Optimization of Hyper-Parameters**:
   - **Advanced Optimization Techniques**: The process of selecting optimal hyper-parameters can be resource intensive. Future work should explore advanced optimization methods, such as automated hyper-parameter tuning techniques (e.g., Bayesian optimization, genetic algorithms) to streamline this process.
   - **Resource Efficiency**: Investigating approaches to reduce the computational resources and time required for hyper-parameter tuning, including parallel computing and cloud-based solutions, will be beneficial.
3. **Variable Selection and Impact Analysis**:
   - **Feature Engineering**: The performance of forecasting models is highly sensitive to the selection of independent variables. Future research should develop systematic approaches for feature selection and engineering to identify the most impactful variables.
   - **Impact Assessment**: Conduct studies to assess how the inclusion or exclusion of specific variables affects model outcomes. This will help in understanding their significance and improving model efficiency.
4. **Geographical and Temporal Scope Enhancement**:
   - **Diverse Regional Data**: The applicability of forecasting models is often limited by the geographical scope of available data. Future research should aim to gather and analyze data from diverse regions to broaden the applicability of the models.
   - **Addressing Temporal Variability**: Incorporating long-term and seasonal data to account for temporal variations in energy trends will enhance model robustness and accuracy.
5. **Development of Hybrid Renewable Energy Systems**:
   - **Integration of Solar and Wind Energy**: Combining solar and wind energy sources in hybrid systems can balance energy supply throughout the day and night. Future research should focus on designing and optimizing forecasting models for hybrid systems to improve efficiency and reliability.
   - **System Design and Optimization**: Explore the design and operational strategies for hybrid renewable energy systems, including energy storage

solutions and grid integration. Research in this area can lead to more efficient and cost-effective energy systems.

6. **Exploration of Advanced Model Architectures**:
    - **Innovative Architectures**: Investigate advanced deep learning architectures, such as attention mechanisms, transformers, and hybrid models, to enhance forecasting accuracy and efficiency.
    - **Ensemble Learning**: Study the application of ensemble learning techniques, where multiple models are combined to improve overall performance and robustness.

5.5 Conclusion

This study has developed and optimized a Deep Dense Network (DDN) model to significantly enhance wind energy forecasting accuracy. The DDN model, featuring dense layers and dropout regularization, demonstrated substantial performance improvements through Grid Search Optimization. Specifically, the Mean Squared Error (MSE) decreased by 94.013% and the MAE improved by 76.8474%. These results highlight the effectiveness of the DDN model in providing precise and reliable wind energy forecasts.

The model's architecture and optimization process have proven superior compared to other neural network approaches, such as LSTM networks and GRUs, showcasing its robustness and efficiency. The study underscores the potential of deep learning techniques to advance wind energy forecasting and support effective resource planning and economic viability assessments for renewable energy projects.

Overall, the findings confirm that the DDN model is a powerful tool for accurate wind energy prediction, offering valuable insights and practical applications for the renewable energy sector.

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Appendix

Code of the proposed DDN Model

Uploading the dataset

```
# Important Libraries
from google.colab import drive
import pandas as pd
from google.colab import files
#Mount the drive
drive.mount('/content/drive')
# GPU information
!nvidia-smi
uploaded = files.upload()
#Read the file
df = pd.read_csv('TexasTurbine.csv')
```

Preprocess the dataset

```
#check for missing values/ cleaning the file
df.isnull().values.any()
```

```
#Visualise the Give n Dataset, Wind speed, Wind Direction, Air
pressure, Air temperature
import matplotlib.pyplot as plt
fig, axes = plt.subplots(nrows=1, ncols=4, figsize=(20, 5))
# Scatter plot of system power generated vs. wind speed
axes[0].scatter(df['System power generated | (kW)'], df['Wind speed
| (m/s)'])
axes[0].set_xlabel('System Power Generated (kW)')
axes[0].set_ylabel('Wind Speed (m/s)')
axes[0].set_title('System Power Generated vs. Wind Speed')

# Scatter plot of system power generated vs. wind direction
axes[1].scatter(df['System power generated | (kW)'], df['Wind
direction | (deg)'])
axes[1].set_xlabel('System Power Generated (kW)')
axes[1].set_ylabel('Wind Direction (deg)')
axes[1].set_title('System Power Generated vs. Wind Direction')

# Scatter plot of system power generated vs. pressure
axes[2].scatter(df['System power generated | (kW)'], df['Pressure |
(atm)'])
axes[2].set_xlabel('System Power Generated (kW)')
axes[2].set_ylabel('Pressure (atm)')
axes[2].set_title('System Power Generated vs. Pressure')
```

```
# Scatter plot of system power generated vs. air temperature
axes[3].scatter(df['System power generated | (kW)'], df['Air
temperature | (\'C)'])
axes[3].set_xlabel('System Power Generated (kW)')
axes[3].set_ylabel('Air Temperature (\'C)')
axes[3].set_title('System Power Generated vs. Air Temperature')
# Adjust the layout
plt.tight_layout()
# Show the plots
plt.show()
```

Split the dataset in training, validation and testing

```
from sklearn.model_selection import train_test_split

# Split the dataset into training and temporary sets (80% for
training + 20% for temporary)
train_temp, test_val = train_test_split(df, test_size=0.2,
random_state=42)

# Split the temporary set into testing and validation sets (50% each
of the temporary set)
test, val = train_test_split(test_val, test_size=0.5,
random_state=42)

# Calculate the percentage of data for each set
total_samples = len(df)
train_percentage = len(train_temp) / total_samples * 100
test_percentage = len(test) / total_samples * 100
val_percentage = len(val) / total_samples * 100

# Print the sizes and percentages of each set
print("Training set size:", len(train_temp),
f"({train_percentage:.2f}%)")
print("Testing set size:", len(test), f"({test_percentage:.2f}%)")
print("Validation set size:", len(val), f"({val_percentage:.2f}%)")
```

```
from sklearn.model_selection import train_test_split

# Split the dataset into training and temporary sets (80% for
training + 20% for temporary)
train_temp, test_val = train_test_split(df, test_size=0.2,
random_state=42)

# Display the dimensions of the sets
print("Training set dimensions:", train_temp.shape)
print("Testing set dimensions:", test.shape)
```

```
print("Validation set dimensions:", val.shape)
```

Proposed DDN model

```
from keras.layers import BatchNormalization
from keras.optimizers import Adam
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense, Dropout
from keras.optimizers import Adam
from keras.callbacks import EarlyStopping

# Preprocess the data
scaler = MinMaxScaler()
scaled_train = scaler.fit_transform(train_temp.iloc[:, 1:])  # Scale
features, excluding the timestamp

# Split the features and target variable
X_train = scaled_train[:, 1:]  # Input features
y_train = scaled_train[:, 0]  # Target variable (system power
generated)

# Scale the test data
scaled_test = scaler.transform(test.iloc[:, 1:])

# Split the features and target variable for testing
X_test = scaled_test[:, 1:]  # Input features
y_test = scaled_test[:, 0]  # Target variable (system power
generated)

# Build the ANN model with increased complexity
model = Sequential()
model.add(Dense(512, activation='relu',
input_shape=(X_train.shape[1],)))
model.add(Dropout(0.4))
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.4))
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.4))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.4))
model.add(Dense(32, activation='relu'))
model.add(Dropout(0.4))
model.add(Dense(16, activation='relu'))
model.add(Dropout(0.4))
model.add(Dense(8, activation='relu'))
```

```
model.add(Dropout(0.4))
model.add(Dense(1))
# Compile and train the model
learning_rate =1e-1
optimizer = Adam(learning_rate=learning_rate)
model.compile(loss='mean_squared_error', optimizer=optimizer,
metrics=['mse', 'mae'])
early_stopping = EarlyStopping(patience=10, verbose=0)
```

Proposed model DDN training

```
# Train the model
history = model.fit(X_train, y_train, epochs=50, batch_size=128,
validation_split=0.1, callbacks=[early_stopping])

# Evaluate the model
y_pred = model.predict(X_test)
mse = np.mean((y_test - y_pred)**2)
mae = np.mean(np.abs(y_test - y_pred))
print("MSE:", mse)
print("MAE:", mae)

# Plot the training and validation loss
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```