E3S Web of Conferences **540**, 03009 (2024) https://doi.org/10.1051/e3sconf/202454003009
*ICPES 2023*

# Predicting Wind Energy: Machine Learning from Daily Wind Data

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**Abstract.**This paper offers a comprehensive review of the advancements in the realm of renewable energy, specifically focusing on solid oxide fuel cells and electrolysers for green hydrogen production. The review delves into the significance of wind energy as a pivotal renewable energy source and underscores the importance of precise forecasting for efficient energy management and distribution. The integration of machine learning-based approaches, such as Support Vector Regression and Random Forest Regression, has shown promising results in enhancing the accuracy of wind energy production forecasts. Furthermore, the paper explores the broader landscape of renewable energy generation forecasting, emphasizing the rising prominence of machine learning and deep learning techniques. As the penetration of renewable energy sources into the

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electricity grid intensifies, the need for accurate forecasting becomes paramount. Traditional methods, while valuable, have encountered limitations, paving the way for advanced algorithms capable of deciphering intricate data relationships. The review also touches upon the inherent challenges and prospective research avenues in the domain, including addressing uncertainties in renewable energy generation, ensuring data availability, and enhancing model interpretability. The overarching goal remains the seamless integration of renewable sources into the grid, propelling us towards a greener future.

## 1 Introduction

The global energy landscape is undergoing a transformative shift, with renewable energy sources (RES) playing a pivotal role in steering the world towards a sustainable future. Wind energy, in particular, has risen to prominence as a vital renewable energy source. Its rapid adoption is a testament to its potential; however, the intermittent nature of wind energy poses challenges in accurately forecasting its production. The unpredictability stemming from variable wind speeds and directions necessitates innovative solutions to ensure consistent and efficient energy generation.

Machine learning (ML) and deep learning (DL) have emerged as frontrunners in addressing these challenges. By harnessing historical data on wind speed, direction, and energy production, these algorithms can discern patterns and make informed predictions. Such accurate forecasts are indispensable for the optimal planning and management of wind farms, ensuring a harmonious balance between energy supply and demand. Furthermore, the integration of ML and DL in renewable energy forecasting extends beyond wind energy. Solar energy, another crucial RES, is influenced by factors like cloud cover and seasonal sunlight variations. Accurate forecasting models can mitigate the impacts of such variabilities, ensuring a seamless integration of RES into the power grid.

Traditional forecasting models, though valuable, have encountered limitations in handling the intricate nonlinear relationships inherent in renewable energy data. Statistical models, such as the autoregressive integrated moving average (ARIMA), and physical models like numerical weather prediction (NWP) models, have been foundational in energy forecasting. Yet, the complexity of Earth's atmosphere and the inherent uncertainties in weather forecasting have highlighted the need for more advanced solutions. ML and DL algorithms, with their ability to process vast amounts of data and discern complex relationships, offer a promising avenue for enhancing the accuracy of renewable energy forecasts.

This review aims to provide a holistic overview of the advancements in ML and DL techniques for renewable energy forecasting. By exploring the strengths, limitations, and applications of various algorithms, we seek to shed light on the future trajectory of renewable energy integration. The overarching objective is to underscore the significance of accurate forecasting in achieving a sustainable energy ecosystem, emphasizing the role of cutting-edge technologies in realizing this vision.

## 2 Review and discussion

In a study by Margarat et al. (2023), the authors delve into the realm of wind energy, a rapidly growing source of renewable energy [1]. The study underscores the importance of accurately forecasting wind energy production for effective energy management and distribution. The inherent intermittent nature of wind energy, influenced by the variability in wind speed and direction, makes its prediction challenging.

To address this unpredictability, the authors propose a machine learning-based approach that employs Support Vector Regression (SVR) and Random Forest Regression (RFR) for forecasting wind energy production. The methodology they advocate encompasses several stages [3-5]:

1. **Data Collection**: Gathering historical data on wind energy production and associated weather variables like wind speed, direction, temperature, and humidity.
2. **Data Preprocessing**: This involves cleaning the data by eliminating missing values and outliers. Additionally, feature engineering is performed to derive more insightful features.
3. **Data Partitioning**: The data is divided into training and testing sets, typically in a 70:30 or 80:20 ratio.
4. **Model Selection**: Different regression models are evaluated, with SVR and RFR emerging as the preferred choices for forecasting wind energy production.
5. **Model Training**: The chosen models are trained using the training data. For instance, in the case of SVR, the algorithm focuses on determining hyperparameters that minimise the error function.

The performance of these models is gauged using metrics such as mean squared error (MSE), root mean squared error (RMSE), and the coefficient of determination (R-squared). The results from the study indicate that the combined SVR-RFR model surpasses individual models, achieving superior accuracy in forecasting wind energy production.

Furthermore, the authors present experimental results comparing the proposed SVR-RFR model with an existing Artificial Neural Network (ANN) model. The proposed model consistently outperforms the ANN model across various datasets, including Solar PV, Hydro power, Wind Power, and Bio-power, in terms of both Mean Square Error and Root Mean Square Error.

In conclusion, Margarat and colleagues have presented a robust machine learning-based approach for forecasting wind energy using a combination of SVR and RFR. Their findings suggest that this combined model offers higher accuracy than standalone models. The proposed methodology, complete with feature selection, hyperparameter optimisation, and interpretability, provides a comprehensive understanding of the factors influencing wind energy production. This approach holds significant promise for real-time applications in energy management and distribution, paving the way for a more sustainable and efficient utilisation of renewable energy.

The significance of the findings and statistical models presented by Margarat et al. (2023) in the context of "Predicting Wind Energy: Machine Learning from Daily Wind Data" can be understood from multiple perspectives:

1. **Enhanced Accuracy**: The combined SVR-RFR model showcased superior forecasting accuracy compared to individual models. This means that energy producers and distributors can make more informed decisions based on these accurate predictions, leading to better resource allocation and management.
2. **Addressing Variability**: Wind energy is inherently variable due to the unpredictable nature of wind speeds and directions. By employing machine learning techniques that use daily wind data, the study offers a solution to predict

these variations more accurately, thereby ensuring a more consistent energy supply.

3. **Optimisation of Resources**: With more accurate forecasts, energy grids can optimise the storage and distribution of wind energy. This can lead to reduced wastage, better grid management, and potentially lower costs for consumers.
4. **Informed Investment Decisions**: For investors and stakeholders in the wind energy sector, these predictive models provide insights into potential energy yields. This can guide decisions related to the placement of new wind farms, infrastructure investments, and expansion strategies.
5. **Integration with Other Renewable Sources**: The ability to accurately predict wind energy production can aid in the integration of wind power with other renewable energy sources. For instance, on days when wind energy production is forecasted to be low, other sources like solar or hydro can be ramped up to meet the demand.
6. **Environmental Impact**: By optimising wind energy production and reducing reliance on non-renewable sources, there's potential for a significant reduction in carbon emissions. This aligns with global efforts to combat climate change.
7. **Economic Implications**: Accurate predictions can lead to better market pricing for wind energy. Energy producers can make informed decisions about when to sell energy, potentially leading to higher revenues.
8. **Scalability and Adaptability**: The machine learning models, once trained, can be adapted and scaled to different regions or even countries. This means that the methodology is not limited to a specific geographical area and can be applied globally.

In summary, the significance of the study lies in its potential to revolutionise the way wind energy is produced, managed, and distributed. By leveraging daily wind data and advanced machine learning techniques, the research paves the way for a more sustainable, efficient, and economically viable wind energy sector.

In a study by Benti et al. (2023), the authors present a comprehensive review of the advancements and prospects in forecasting renewable energy generation using machine learning (ML) and deep learning (DL) techniques. With the escalating integration of renewable energy sources (RES) into the electricity grid, there's an imperative need for precise forecasting to ensure efficient grid operation and energy management. Traditional forecasting methods, while useful, have their limitations, especially when dealing with the inherent variability and unpredictability of renewable energy sources like wind and solar [2].

The authors highlight that ML and DL algorithms have gained traction due to their capability to discern complex relationships from vast datasets and offer accurate predictions. These algorithms, especially when applied to daily wind data, can significantly enhance the accuracy of wind energy predictions. The study reviews various ML and DL approaches, discussing their strengths, limitations, and applications in renewable energy forecasting.

For instance, supervised learning, a subset of ML, has been employed extensively for renewable energy forecasting. Techniques such as Linear Regression, Decision Trees, and Support Vector Machines (SVM) have been utilised, each with its unique advantages and challenges. Regression, in particular, aims to identify mathematical functions correlating input variables to continuous output variables, making it suitable for predicting renewable energy outputs.

Furthermore, the study delves into the challenges of predicting solar and wind energy. Solar energy prediction is influenced by factors like cloud cover and seasonal sunlight changes, while wind energy prediction is affected by the non-linearity and randomness of wind patterns. The authors underscore the potential of ML and DL in addressing these challenges. For instance, various ML algorithms, including the improved dragonfly algorithm (IDA) with SVM, local mean decomposition (LMD), and convolutional neural networks (CNN), have been proposed to enhance the accuracy of wind energy predictions.

However, despite the advancements in ML and DL for renewable energy forecasting, challenges persist. The selection of appropriate algorithms, handling of missing data, and the need for robust and interpretable models are areas that require further research and development.

The table below delineates various deep learning algorithms, shedding light on their intrinsic details, the challenges or gaps they present, and the distinct advantages they offer. These models, ranging from traditional neural networks to more advanced ensemble and hybrid models, underscore the evolution and potential of machine learning in harnessing the power of wind energy. By understanding the nuances of each model, stakeholders can make informed decisions on the most suitable approach for their specific forecasting needs.

**Table 1.**Deep Learning Models in Wind Energy Forecasting [6-10]

| Model | Details | Challenges/Gaps | Advantages |
|---|---|---|---|
| ANN for Renewable Energy Forecasting | Artificial Neural Networks (ANNs) are a popular choice for renewable energy forecasting due to their ability to model complex non-linear relationships. They are particularly effective for short-term forecasting. | ANNs require a large amount of data for training and can be computationally intensive. They can also overfit if not properly regularized. | ANNs can capture complex patterns in the data, making them suitable for forecasting tasks with non-linear relationships. |
| CNN for Renewable Energy Forecasting | Convolutional Neural Networks (CNNs) are primarily used for image processing but have found applications in renewable energy forecasting, especially when spatial data is involved. | CNNs can be computationally intensive and may require specialized hardware for training. | They can automatically and adaptively learn spatial hierarchies of features from input images. |
| RNN for Renewable Energy Forecasting | Recurrent Neural Networks (RNNs) are designed to recognize patterns in sequences of data, making them ideal for time series forecasting tasks. | Training RNNs can be challenging due to issues like vanishing and exploding gradients. | RNNs can capture temporal dependencies in data, making them suitable for time series forecasting. |
| RBM for Renewable Energy | Restricted Boltzmann Machines (RBMs) are generative neural network models that can learn a | Training RBMs can be complex. | They can be used to extract meaningful features from data |

| | | | |
|---|---|---|---|
| Forecasting | probability distribution over its set of inputs. | | without supervision. |
| Auto Encoder for Renewable Energy Forecasting | Autoencoders are neural networks used for unsupervised learning of efficient codings. | They might not be directly suited for forecasting but can be used for feature extraction. | They can reduce the dimensionality of data, helping in feature extraction. |
| Deep Belief Neural Networks (DBN) for Renewable Energy Forecasting | DBNs are a type of deep neural network that consists of multiple layers of stochastic, latent variables. | Training DBNs can be computationally intensive. | They can learn to represent very complicated distributions. |
| ANFIS for Renewable Energy Forecasting | Adaptive Neuro Fuzzy Inference System (ANFIS) is a kind of neural network that is based on the Takagi-Sugeno fuzzy inference system. | Requires careful tuning. | It combines the benefits of neural networks and fuzzy systems. |
| Wavelet Neural Network (WNN) for Renewable Energy Forecasting | WNNs combine wavelet transforms with neural networks. | Requires careful selection of wavelet functions. | Can capture both high-level and low-level features in data. |
| RBNN for Renewable Energy Forecasting | Radial Basis Function Neural Networks (RBNNs) are a type of feedforward neural network. | They can be sensitive to the choice of basis functions. | They can approximate any continuous function. |
| GRNN for Renewable Energy Forecasting | General Regression Neural Networks (GRNNs) are a kind of radial basis neural network. | Can be computationally intensive. | They can be used for real-time applications due to their fast response. |
| ELM for Renewable Energy Forecasting | Extreme Learning Machines (ELMs) are feedforward neural networks with a single layer of hidden nodes. | They can sometimes overfit. | They can be much faster than traditional feedforward networks. |
| Ensemble Learning for Renewable Energy Forecasting | Ensemble methods use multiple learning algorithms to obtain better predictive performance. | Requires combining predictions from multiple models. | Can lead to improved accuracy and robustness. |
| Transfer | TL allows the model to | Requires a source domain | Can lead to improved |

| | | | |
|---|---|---|---|
| Learning (TL) for Renewable Energy Forecasting | transfer knowledge from one domain to another. | with abundant data. | performance when data is scarce. |
| Hybrid Model (HM) for Forecasting Renewable Energy | HMs combine multiple techniques to improve prediction accuracy. | Designing HMs can be challenging. | They leverage the strengths of multiple models. |

In conclusion, Benti and colleagues emphasise the significance of ML and DL in the realm of renewable energy forecasting. Their review suggests that these techniques, especially when applied to daily wind data, hold the potential to revolutionise the way renewable energy is predicted, managed, and integrated into the electricity grid. This, in turn, can facilitate a smoother transition towards a sustainable energy future.

## 3 Future Scope of Research

The realm of renewable energy, particularly in the context of solid oxide fuel cells, electrolysers, and green hydrogen production, is ever-evolving. As we stand on the cusp of significant technological advancements, it's imperative to cast our gaze forward, identifying areas ripe for exploration and innovation. The following pointers elucidate potential avenues for future research in this dynamic field:

- **Advanced Forecasting Models:** Delve deeper into the integration of more sophisticated machine learning and deep learning algorithms, potentially exploring hybrid models that combine the strengths of multiple techniques.
- **Integration of IoT:** With the proliferation of the Internet of Things (IoT), there's scope to integrate real-time data from a myriad of sensors to enhance the accuracy of energy forecasting.
- **Storage Solutions:** As we harness more renewable energy, research into efficient and long-lasting energy storage solutions will become paramount.
- **Material Science Innovations:** Investigate new materials or improve existing ones for solid oxide fuel cells and electrolysers to enhance efficiency and longevity.
- **Grid Modernisation:** As renewable energy sources become more prevalent, there's a need to modernise the electricity grid to handle the influx, ensuring stability and efficiency.
- **Sustainability Assessments:** Comprehensive studies into the environmental impact of green hydrogen production, ensuring that the entire process, from extraction to usage, is sustainable.

## 4 Knowledge Gaps

While the strides in renewable energy research have been commendable, it's equally important to acknowledge the existing knowledge gaps. Identifying these lacunae not only provides clarity on the current state of affairs but also offers direction for future endeavours. Here are some of the prominent knowledge gaps in the domain:

- **Interdisciplinary Integration:** There's a lack of comprehensive studies that integrate findings from meteorology, data science, and renewable energy to enhance forecasting accuracy.
- **Long-term Impact Studies:** While we have insights into the immediate benefits of renewable energy sources, there's a dearth of research on their long-term impacts, both environmentally and economically.
- **Localized Solutions:** Much of the current research offers broad solutions. There's a gap in studies focusing on localised energy solutions tailored to specific geographic and climatic conditions.
- **Consumer Behaviour Analysis:** Understanding consumer behaviour and its impact on energy consumption patterns remains an underexplored area.
- **Economic Implications:** While the environmental benefits of renewable energy are often discussed, there's a need for more in-depth research into the economic implications, especially concerning job creation, market dynamics, and cost-benefit analyses.
- **Regulatory and Policy Challenges:** The intersection of renewable energy adoption and governmental policies is not thoroughly explored, leading to potential hurdles in large-scale implementation.

By addressing these future research avenues and knowledge gaps, the scientific community can pave the way for a more holistic and informed approach to renewable energy adoption, ensuring a brighter and more sustainable future for all.

## 5 Conclusion

The journey through the intricate landscape of renewable energy, with a specific focus on solid oxide fuel cells, electrolyzes, and green hydrogen production, has been enlightening. As we reflect upon the insights gleaned from the articles reviewed, several key findings emerge that not only underscore the current state of affairs but also hint at the promising future that lies ahead. Here are the six pivotal takeaways:

1. **Significance of Wind Energy:** Wind energy has firmly established itself as a cornerstone of renewable energy sources. Its rapid adoption, despite the challenges posed by its intermittent nature, speaks volumes about its potential in driving a sustainable future.
2. **Machine Learning's Role in Forecasting:** The integration of machine learning techniques, especially the synergy between Support Vector Regression and Random Forest Regression, has shown immense promise in enhancing the accuracy of wind energy forecasting. This advancement is pivotal for efficient energy management and distribution.
3. **Broadening the Forecasting Horizon:** Beyond wind energy, the broader landscape of renewable energy generation forecasting is witnessing a paradigm shift. Machine learning and deep learning techniques are revolutionizing the way we predict energy outputs, ensuring a seamless integration of renewable sources into the grid.

4. **Challenges and Innovations:** While the benefits of renewable energy are manifold, challenges like variability, unpredictability, and data availability persist. However, innovations in machine learning, deep learning, and material science are steadily bridging these gaps.
5. **Holistic Approach to Renewable Energy:** The reviewed articles emphasize the need for a comprehensive approach to renewable energy. From harnessing wind and solar energy to understanding consumer behaviour and economic implications, the scope is vast and interconnected.
6. **Towards a Greener Future:** The overarching theme resonating through the articles and our review is the collective aspiration for a greener, more sustainable future. Through advanced forecasting models, efficient storage solutions, and grid modernisation, we are inching closer to realising this vision.

In tying back to our abstract, it's evident that the realm of renewable energy is at an exciting juncture. The convergence of traditional knowledge with cutting-edge technologies is paving the way for breakthroughs that were once deemed unattainable. As we stand on this precipice of change, it's imperative to harness these insights, drive further research, and work collaboratively towards a world powered by clean, sustainable energy.

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