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Predictive Modelling Of Energy Demand And Integration Of Renewable Energy Sources Through Hybrid Approaches

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This research focuses on the modeling of energy demand predictability, along with the integration of renewable sources of energy, such as wind and solar through hybrid approaches. This study seeks to develop a new hybrid predictive model for energy demand forecasting with precise and effective predictions through the integration of traditional energy forecasting techniques and renewable energy sources, including wind and solar. The model will address the challenges posed by the intermittent and erratic nature of renewable energy generation, assessing how hybrid strategies can help stabilize the grid while optimizing energy distribution. The study seeks to improve the accuracy and adaptability of energy demand forecasts using advanced artificial intelligence and machine learning techniques, enabling more reliable integration of renewable energy sources. Moreover, the study will examine the economic and environmental impacts of integrating energy storage systems with smart grid technology and hybrid energy models. This will be conducted to improve resource optimization while minimizing reliance on fossil fuels. The entire study will be based on an all-inclusive framework for the implementation of hybrids forecasting models using different approaches such as statistical, machine learning, and physical methodologies to improve the reliability, sustainability, and efficiency of energy systems. In summary, the study focuses on developing sustainable, resilient, and economically feasible energy systems, which are part of the shift toward renewable sources but ensure stability on the grid as well as environmentally friendly effects. A framework with data-based considerations to aid the transition to more sustainable and secure energy systems.

***Keywords**: Forecasting Accuracy, Hybrid Renewable Energy System (HRES), Solar, Wind Power, Wind-Solar Hybrid System, Machine Learning (ML).*

I. INTRODUCTION

Climate change, security of energy supplies, and sustainability require the global commitment to move out of traditional sources of energy toward cleaner, efficient, and renewable sources of energy. Predictive modelling of energy demand is imperative for understanding patterns of energy use in societies, in industries, and in homes. Accurate prediction of energy demand allows for optimizing generation, storage, and distribution of electricity to assure grid stability while integrating renewable sources of energy more efficiently.

An integration challenge arises because the energy sources from solar, wind, hydro, and geothermal are intermittent and variable, making their combined state uncertain. However, by combining demand-side management strategies, energy storage devices, and predictive modelling across various renewable energy sources, hybrid approaches are becoming viable solutions that will make energy networks more sustainable, robust, and efficient.

Hybrid models normally integrate the principles of machine learning algorithms, artificial intelligence, and optimization techniques, thereby maximizing energy forecast accuracy and proper resource allocation along with an integrative flow for different inputs coming from various forms of renewable sources. Hybrids thus surpass single energy systems on the advantages level. They can predict energy demand while forecasting output from renewable sources, balance supply and demand effectively, integrate energy storage systems, and implement smart grids for dynamic load balancing.

By reducing reliance on fossil fuels and greenhouse gas emissions, hybrid models also provide less expensive energy management options. By accurately forecasting energy demand and maximising the use of renewable energy sources, the models reduce the need for backup fossil fuel generation, which benefits the economy and the environment. The flexibility and stability of energy systems are also enhanced by hybrid models, which allow them to react to unforeseen circumstances with little interruption to customers or downtime.

1.1. CHALLENGES IN INTEGRATING RENEWABLE ENERGY SOURCES

Several major integration issues are also faced with renewable energy sources integrating with the existing power grid and energy system. Although the use of solar, wind, and hydroelectric power offers the benefits of lower environmental pollution as compared to other fossil fuels, variability and intermittency that exist within their intrinsic characteristics plus the geoFigureical limitation imposed create more challenging problems for smooth integration. Some of the main challenges associated with the integration of renewable energy sources into modern energy grids are listed below:

1. **Variability and Intermittency**: Renewable energy source generation is less predictable and comes with reliance upon environmental factors, which include sun for sunlight and wind power. It implies difficulty in achieving continuous energy supply without storage systems as well as inflexible backup options.

2. **Grid Stability and Reliability**: Unwanted frequency and voltage imbalances in the grid would result from renewable energy's intermittent nature. Traditionally designed grids, meant for stable generation, require redesigning to accommodate such variability, involving advanced inverters and better grid management systems.

3. **Energy Storage**: Technologies that will be efficient for the storage of excess energy in periods of low generation need to be developed. Although promising, large-scale cost-effective storage solutions remain a significant challenge.

4. **Transmission and Distribution Constraints**: Renewable energy often comes from a faraway place, well away from a demand center. It requires extensive infrastructure for transmission. This can be expensive and even hindered by the regulatory process.

5. **Economic and Financial Barriers**: Even though renewable technologies are getting cheaper, the high cost of initial investment in infrastructure, storage systems, and grid upgrades continues to exist. Financial incentives and policy stability will be needed to overcome these costs.

6. **Regulatory and Policy Challenges**: The current regulations might not support the integration of renewable energy, as problems such as access barriers in the grid and misaligned policies will cause a halt in the transition towards renewables. Coordination across borders for international grids adds complexity.

The solutions require technological breakthroughs, investments in infrastructure, and new regulatory regimes to fully and effectively integrate renewables into the grid.

Figure 1.1: Renewable Energy Sources.

1.2. HYBRID APPROACHES IN ENERGY SYSTEMS

Hybrid approaches in energy systems consider the use of more than one source of energy generation, technologies, and predictive models for maximally efficient energy generation, for optimization of efficiency, and to increase overall energy system reliability. In order to address the difficulties in operating renewable energy sources and managing the supply and demand for energy, the majority of hybrid models combine conventional and renewable energy sources, energy storage, and smart grid technology.

Hybrid models pave a pathway to an increasingly sustainable and resilient energy infrastructure through leveraging various systems' and technologies' strengths. It can connect multiple, dissimilar sources of energy together into a highly integrated energy network for increased flexibility and much better energy management.

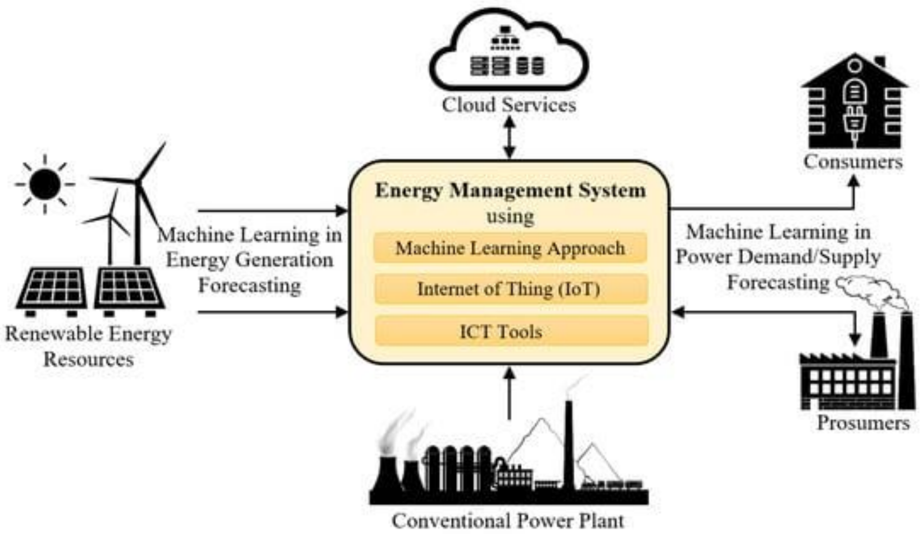

Figure 1.2: Usages of advanced technologies in hybrid-renewable-energy system (HRES).

1. Integration of Renewable and Conventional Energy Sources

Hybrid systems combine traditional energy sources like coal or natural gas with renewable energy sources like solar or wind. By guaranteeing a steady supply of power, it helps to counteract the intermittent nature of renewable energy. Conventional sources provide as a backup and lower emissions during times when renewable generation is scarce.

2. Renewable Energy and Energy Storage Systems

Hybrid systems couple energy storage with renewable generation to capture the excess energy that is produced at times of peak generation. Pumped hydro and other battery-type storage solutions will be available to release the energy when renewable output is low. This smooths the supply and improves grid stability.

3. Microgrids and Hybrid Power Systems

Microgrids merge renewable energy and backup power generation, for instance, from diesel generators, in an effort to generate reliable power for distant or off-grid locations. Independent operation of microgrids has intelligent energy management that optimizes generation and consumption.

4. Hybrid Energy Storage and Generation Systems

Hybrid systems combine a mix of different storage technologies with renewable generation, including battery banks paired with thermal storage. In doing so, hybrid systems eliminate both short-term and long-term variation in renewable generation while providing constant and stable power supply.

5. Hybrid Systems for Peak Shaving and Load Management

Hybrid energy systems reduce peak demand and manage energy loads through the use of stored energy or flexible generation. It helps in saving peaking power plants that consume inefficiently, hence keeping supply in equilibrium with demand, making it optimal in grid efficiency.

6. Optimization and Control Algorithms

In hybrid systems, which involve multiple energy sources and storage, advanced control algorithms are essential. EMS and predictive analytics ensure the efficient production and consumption of energy in hybrid power systems, making the overall performance better.

7. Hybrid Systems in Urban and Rural Areas

Hybrid systems can be customized to fit either urban or rural environments. Urban systems may incorporate solar, battery storage, and smart grids, while a rural system could include renewable sources combined with a backup generator for off-grid reliable energy access.

1.3. PREDICTIVE MODELLING TECHNIQUES FOR ENERGY DEMAND

Predictive modelling techniques are important in energy demand forecasting and ensuring that power systems are operated efficiently and reliably. Using advanced computational models, these techniques enable utilities and energy providers to predict future energy needs, optimize resource allocation, and integrate renewable energy sources. Several predictive modelling techniques are applied in energy demand forecasting, with their strengths and applications. Below are some of the key predictive modelling techniques applied in energy demand forecasting:

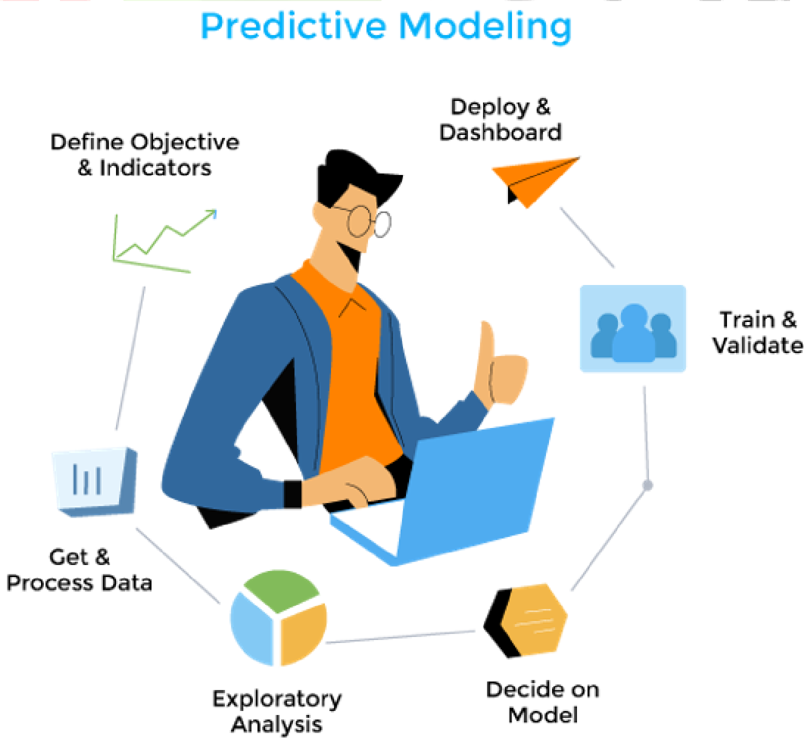

Figure 1.3: Prediction Modelling Techniques.

1. Time Series Analysis

A. A technique is used with historical data for time series analysis, identifying trends and patterns. Methods used in short-term forecasting include ARIMA and seasonal decomposition. This is very useful in identifying the seasonal and cyclical behavior prevailing for energy demand.

2. Regression Analysis

Regression analysis models explain the link between energy consumption and its determinants, such as economic activity, temperature, and time of day. It is appropriate for medium-term forecasting since linear and multiple regression techniques measure the impact of these variables on energy use.

3. Machine Learning Algorithms

Complex and nonlinear correlations in energy demand data can be modelled by machine learning techniques including artificial neural networks (ANN), support vector machines (SVM), decision trees, and random forests. As a result, those models are ideal for learning long-term details of precisely forecasting demand using very vast datasets.

4. Artificial Intelligence and Deep Learning

The most appropriate AI and deep learning methods to capture complex patterns and dependencies in energy consumption are DNN and LSTM networks. These techniques model long-term trends and can deal with large, high-dimensional datasets, which enhance prediction accuracy.

5. Ensemble Methods

Bagging and Boosting, under Ensemble Methods use multiples models so to provide improvements upon forecast and minimize error prediction on increasing its strength of decision - therefore in robust forecasting concerning Energy demand.

6. Hybrid Models

Hybrid models combine the strengths of various predictive techniques by combining different predictive techniques such as ARIMA with ANN or SVM with deep learning. This further enhances the precision and efficiency in the predictions made regarding energy demand.

7. Big Data Analytics and IoT Integration

Big data analytics and IoT technologies help to collect and analyze data in real time, improving predictive models. Smart meters and sensors provide detailed insights on consumption patterns that help energy providers improve their forecasting and, thus, better decision-making and energy management.

1.4. FORECASTING RENEWABLE ENERGY OUTPUT

Renewable energy forecasting is essential to incorporate renewable sources, such as solar, wind, and hydropower, into the grid. Renewable generation is intermittent and varies with time. Accurate forecasting of renewable generation ensures the stability, reliability, and proper distribution of energy in the grid. Predictive techniques are applied to estimate energy output from renewable sources over various time horizons. Such forecasts assist grid operators in anticipating supply fluctuations, managing energy storage, and maintaining supply-demand balance.

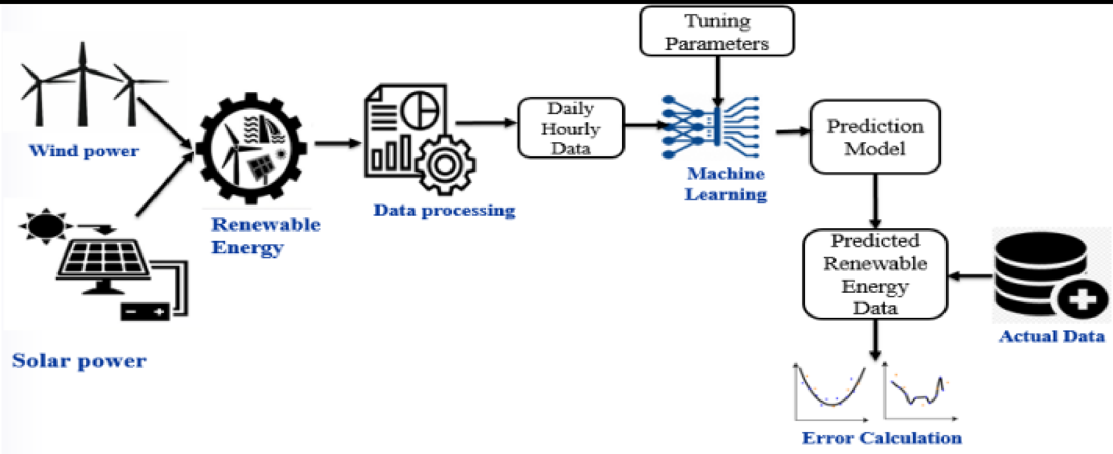

Figure 1.4: Renewable Energy Forecasting Model.

1. Importance of Forecasting Renewable Energy Output

The main challenge associated with renewable sources of energy such as solar and wind is its inherent uncertainty. Weather, day, and time of year lead to massive generation fluctuations. Therefore, forecasting of these variables has helped the operators of the grids to handle fluctuations by planning their periods of peak or troughs. It further helps them plan for integrating those sources of energy with conventional ones, optimize their storage systems, and decrease dependency on fossil fuel.

2. Methods of Renewable Energy Output Forecasting

This ranges from statistical, machine learning approaches, to even hybrid approaches of forecasting renewable energy output.

- **Statistical Methods**: The traditional methods adopted include time series analysis, that is, ARIMA, and regression models. These helps predict patterns based on historical data such as energy output seasonality and trends.
- **Machine Learning Models**: With ANN, SVM, and decision trees, for instance, are advanced techniques for catching the subtle interaction of weather conditions, geo Figurey, and power production. It has a big chance to be utilized for learning a lot of information in datasets. It will really work effectively with real-time data for forecasts.
- **Hybrid Models**: Hybrid models combine different forecasting methods for higher accuracy and reliability. For example, by combining machine learning with time series analysis, predictions can be enhanced by utilizing the strengths of historical data and sophisticated data-driven insights.

3. Weather Forecasting for Renewable Energy

Weather conditions are a primary factor affecting renewable energy production, especially in the case of solar and wind energy. Accurate prediction of wind speed, cloud cover, temperature, and precipitation is critical to predicting energy generation. Meteorological models, satellite data, and weather stations serve as inputs for energy generation predictions that help in short-term and medium-term forecasting.

- **Solar Energy**: For solar energy, the key inputs are cloud cover and levels of solar radiation. Weather models are used in solar forecasting to predict cloud cover, which impacts the efficiency of solar panels.

- **Wind Energy**: Forecasting for wind energy depends on the prediction of wind speed and wind direction. Wind farms are typically sited in areas with strong wind potential, but some local variations influence wind behavior, so forecasting is somewhat demanding.

4. Short-term vs Long-term Forecasting

For any time horizon, the forecast of renewable energy output is different.

- **Short-term Forecasting (Hours to Days)**: This forecasting is based on energy output predictions in the short run, like a few hours or days ahead. It allows the grid operators to adjust their supplies to the sudden change in demand and supply. Near-term techniques for making these predictions include real-time weather data, machine learning, and time series models.

- **Medium and Long-term Forecasting (Weeks to Months)**: This medium and long-term forecasting is quite important for strategic planning as well as for seasonal fluctuation understanding of renewable energy output. Thus, these forecasts help in capacity planning, maintenance scheduling, and optimization of energy storage systems.

5. Challenges in Forecasting Renewable Energy Output

Despite the progress made in forecasting techniques, several challenges remain in predicting renewable energy output:

- **Intermittency**: Solar and wind sources are intermittent. There will be periods of overproduction or underproduction, and the unpredictability of these sources makes it hard to match supply with demand.

- **Data Availability and Quality**: The quality of the forecast made mainly depends on data including weather data and historical data on energy production. Inaccurate or incomplete data may lead to mistakes in forecasting.

- **GeoFigureical Variability**: Weather conditions in different locations may vary to such an extent that a model applicable to all sources of renewable energy may not be applied uniformly.

6. Role of Energy Storage and Grid Management

Renewable energy requires energy storage systems, including pumped hydro and batteries, in order to level the intermittent generation from renewable energy. Therefore, it enables the determination of whether to store extra energy when output exceeds the amount needed, or to let out stored energy in the grid for a supply/demand balance. Proper prediction leads to optimal use of energy storage systems for balancing the grid.

7. Future Trends in Renewable Energy Forecasting

Technology advances to better improve renewable energy forecasting by precision and efficiency. It's with the introduction of artificial intelligence, big data analytics, and real-time processing that has facilitated precise prediction. More advancement on the development of intelligent grid systems with algorithms on better forecasting would eventually facilitate renewable energy into the power grid with minimal dependency on fossil fuel energy sources while being clean and more sustainable in its operations.

1.5. SIGNIFICANCE OF THE STUDY

This study's importance in energy demand prediction modelling and hybrid approaches to renewable energy integration originates from its capacity to address some of the most difficult issues facing contemporary energy systems. The goal of a hybrid predictive model is to improve the accuracy and efficiency of energy demand prediction by combining conventional forecasting techniques with renewable energy sources like solar and wind. The study explores how grid stability and reliability might be attained by using hybrid solutions to handle the erratic and unpredictable character of renewable energy output. Additionally, it highlights cutting-edge machine learning and artificial intelligence methods for improving the accuracy and adaptability of predictive models for renewable energy integration. Thus, in an effort to optimise resources and reduce the use of fossil fuels, the study evaluates the economic and environmental advantages of combining energy storage and smart grid technologies into a hybrid system. Actually, the goal of this project is to develop a comprehensive framework for statistical, machine learning, and physical approaches to build dependable and sustainable energy systems that solve the issues of energy security and environmental sustainability.

1.6. NEED AND SCOPE OF THE STUDY

This study is necessary due to the complexity of contemporary energy systems, where integrating renewable energy sources—such as solar and wind—presents particular difficulties due to its erratic and intermittent nature. For this reason, predictive modelling must be as accurate as feasible in order to ensure grid stability, optimise resource allocation, and reduce dependency on fossil fuels. In order to meet this need, the study suggests a hybrid strategy that enhances the precision and adaptability of energy demand forecasts by fusing cutting-edge approaches like artificial intelligence and machine learning with conventional forecasting methodologies. Furthermore, it addresses smart grid and energy storage technologies as crucial elements for enhancing system performance and mitigating negative environmental effects. In order to produce sustainable, dependable, and cost-effective energy solutions that enable the clean energy transition while preserving grid stability and efficiency, this study will concentrate on creating a broad framework that is empirically, statistically, and machine learning-based.

1.7. STATEMENT OF THE PROBLEM

The problem that the current study focuses on is related to the fact that it becomes increasingly complex to predict energy demand with sufficient accuracy while incorporating renewable sources such as wind and solar power, which are inherently intermittent and hard to predict. Conventional forecasting techniques fail to deliver the required level of precision and adaptability, especially in cases where renewable sources are involved, thus posing significant challenges for the stability of the grid, optimizing resource allocation, and reducing fossil fuel dependency. Further, non-availability of hybrid models using highly advanced technologies that include artificial intelligence, machine learning, energy storage systems, smart grids, complicates the ability to find viable and reliable approaches toward sustainable and clean energy options. The scope of this work is thus devised to propose a traditional, statistical machine learning, as well as the physical approach integrated predictive modelling for overcoming the posed challenges. For instance, exact energy forecasting for enhanced grid reliability and betterment of economic, environmental results shall be obtained.

1.8. RESEARCH OBJECTIVES

The study's goals are to:

- To create a hybrid predictive model that combines conventional energy forecasting techniques with renewable energy sources, such as wind and solar, to guarantee precise and effective.
- To assess how well hybrid strategies, handle the erratic and intermittent nature of renewable energy production and how they affect grid stability.
- To assess how cutting-edge artificial intelligence and machine learning methods might enhance the accuracy and flexibility of predicted energy demand models for the integration of renewable energy sources.
- To evaluate the financial and ecological advantages of incorporating energy storage and smart grid technology into hybrid energy systems in order to optimise resource allocation and lessen reliance on fossil fuels.
- To provide a thorough framework for putting into practice hybrid forecasting models that improve the sustainability and dependability of energy systems by combining statistical, machine learning, and physical techniques.

II. LITERATURE REVIEW

. **Ukoba et al. (2024)**provided a comprehensive analysis of AI and renewable energy (RES) integration in power grids, focusing on key approaches, challenges, and achievements. The integration of RES has increased due to the global shift towards sustainable energy sources, and the synergistic application of AI techniques is becoming a feasible way to enhance their effectiveness, dependability, and economic feasibility. The paper presents various AI applications in optimizing aspects of RES, including grid integration, resource evaluation, energy forecasting, system monitoring, and control techniques. It aims to understand the role of machine learning algorithms, neural networks, and optimization approaches in complex data sets in improving predictive capacities and dynamically adapting RES. The paper also addresses problems related to AI implementation in RES, such as real-time adaptability, model interpretability, and data variability. The future of the field is examined, considering new developments and the potential influence of emerging AI developments on optimizing RES systems.

Ncir and Akchioui (2024)aimed to create a hybrid intelligent maximum power point tracking (MPPT) regulator using an artificial neural network model and a new optimization technique from the fireworks algorithm (FWA). The ANN configuration situations were evaluated for different training algorithms and hyperparameter values to converge towards the optimal objective function. The efficiency of the chosen FWA–ANN model under various partial shading situations was demonstrated by simulating it as an MPPT controller using MATLAB/Simulink software and comparing it to the most popular MPPT techniques. The results showed that the proposed FWA–ANN scheme, using BR and four neurons at the hidden layer, achieved the best mean-squared error of 2.74e13 throughout training and 0.1159 after each optimization period. The model outperformed the most popular MPPT methods, reaching a power efficiency of over 99.5749% and significantly reducing oscillations in transient and steady states.

Sharifhosseini et al. (2024)explored the importance and challenges of forecasting renewable energy in electrical power networks, which are crucial for modern infrastructure and the world's growing reliance on electricity. It provides a comprehensive overview of electrical power systems and the critical roles of forecasting and optimization in ensuring sustainability. The article reviews various optimization techniques for power systems, including network reconfiguration, optimal power flow, unit commitment, and economic dispatch. It discusses classical and recent approaches, such as meta-heuristics algorithms and AI-based methods. The review highlights how accurate forecasts can efficiently upgrade optimization techniques. Electrical engineers should use this review in designing advanced forecasting and optimization methods, ensuring environmental issues are addressed, consumer behavior changes, reliable efficiency, and a sustainable future in energy use.

Kiasari et al. (2024)examined the use of Machine Learning (ML) techniques in energy management optimization in smart grids. It emphasizes the importance of integrating renewable energy sources (RES) like solar and wind to achieve energy sustainability. The paper highlights the role of RES in reducing greenhouse gas emissions and supporting environmental sustainability and energy security. It also explores the development of smart grid technologies like Distributed Control Systems, Advanced Metering Infrastructure, and Supervisory Control and Data Acquisition systems. The paper highlights the transition towards a sustainable energy future by merging RES and smart grid technology, emphasizing the need for innovation and supportive legislative frameworks. The paper emphasizes the transition momentum towards a sustainable energy future and the need for innovation and supportive legislative frameworks.

Hanif and Mi (2024)examined the development of transformer models in solar forecasting, a synthesis of machine learning and renewable energy research. It evaluates the performance of various transformer topologies, including single, hybrid, and specialized models, and demonstrates their ability to handle complex solar data. The review highlights significant gains in forecasting accuracy and computing efficiency, but also highlights the importance of hyperparameters in fine-tuning model performance. The paper also highlights barriers to the broader use of these models, such as computational resources and large, high-quality datasets. It recommends future studies focus on standardizing model configurations, pursuing longer-term forecasting, and encouraging innovations to improve computational economy. The paper outlines the current state of transformer models in solar energy forecasting and suggests future directions to achieve more precise, flexible, and sustainable solar forecasting methods. This guidebook would help researchers and practitioners develop reliable and efficient renewable energy systems by summarizing current advancements and future directions in solar data interpretation and forecasting.

III. RESEARCH METHODOLOGY

The chosen research methodology in the study entails a detailed study of the hybrid renewable systems' energy production and consumption patterns, especially with respect to the combined solar and wind power outputs. For the assessment of the efficiency of hybrid systems and the accuracy of energy forecasts, the technique comprises two critical parts: data gathering and analysis.

1.1. Data Collection

Data for the research came from a wind and solar hybrid energy system that had been operational for several time periods and maintained records of energy use and output. Data on the production of solar and wind energy included output of solar energy, output of wind energy, overall energy output, and energy consumption at hourly intervals. These values were then used to calculate the mean, standard deviation, minimum, and maximum for each parameter, thereby allowing a detailed look at the performance of the system over a wide range of time periods. The energy output data was also matched against predicted values to determine the degree of accuracy in the system's predicting capability.

1.2. Energy Production and Consumption Analysis

This included first analyzing the figures of energy produced and consumed in the hybrid system. Through calculating the mean, standard deviation, minimum, and maximum values of the energy output, both from the solar and wind sources, the analysis was done to evaluate the overall performance of the system. The variation in energy output and consumption was studied to ascertain the degree of fluctuation and evaluate the system's capacity to satisfy energy demand over various time periods. The results were analyzed to determine the system efficiency and variables affecting energy production and consumption.

1.3. Forecast vs Actual Energy Output Comparison

The second part of the methodology compared the predicted and actual energy output of the hybrid system at different times of the day. This step checked the accuracy of the system's energy forecast. For each time interval, the percentage inaccuracy was calculated by comparing the hourly predicted and actual energy production. The error values were used in the evaluation of the accuracy of the forecasting model and the times when there existed differences between the expected and the actual outputs. The study looked at assessing the accuracy of energy forecasting by the system by grasping the margins of error that existed at several periods of the day.

1.4. Statistical Methods and Data Interpretation

Statistical techniques comprising the calculation of mean, standard deviation, and percentage error had been used for ensuring the legitimacy and reliability of results. These statistics have revealed more about the global accuracy and performance capability of the hybrid system. For identifying tendencies in predicting the accuracy and making it possible to further highlight the advantageous and weak facets of the system, the comparing data of forecasts with actual outputs were analyzed. To further facilitate the comprehension of the findings and allow easier interpretation of the results, the outcomes were presented graphically.

2. DATA ANALYSIS

The table of statistics for production and consumption in hybrid systems will be given next, with figures on energy yields from wind power and solar energy as well as the total energy generated and consumed in the system. The table reflects a complete scenario of the behavior of the system by displaying its mean, standard deviation, minimum, and maximum values for all parameters.

Table 1: Energy Production and Consumption Statistics for Hybrid Systems.

Parameter	Mean	Std. Dev.	Min	Max
Solar Energy Output (kW)	500	120	300	700
Wind Energy Output (kW)	350	100	200	600
Total Energy Output (kW)	850	150	500	1300
Energy Consumption (kWh)	700	180	400	1100

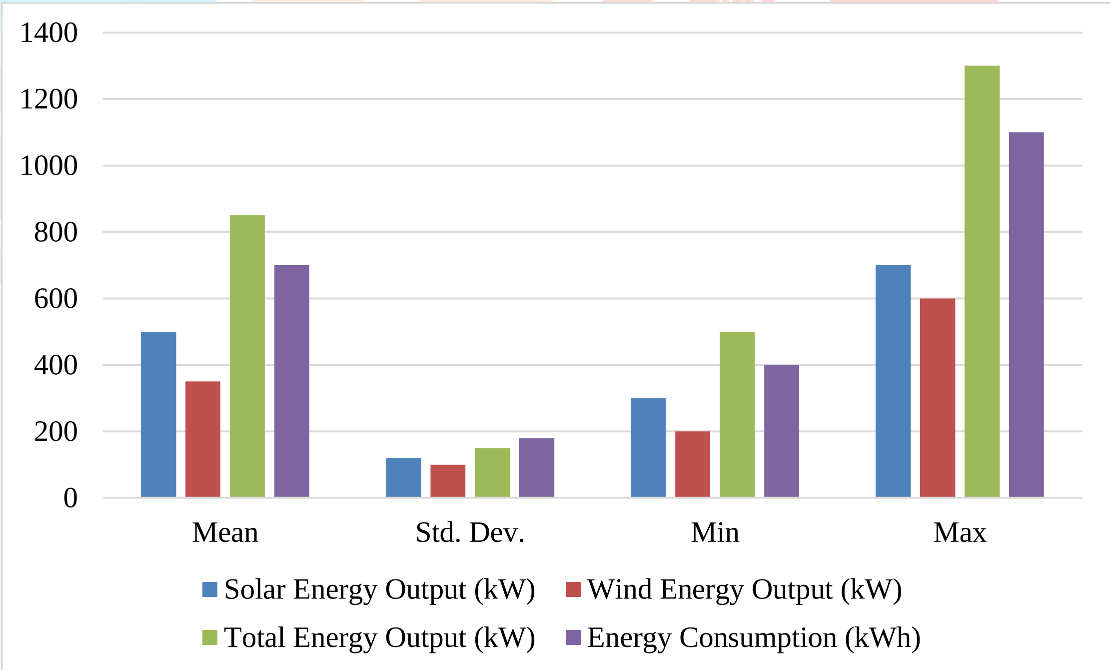

Figure 1: Graphical representation of Energy Production and Consumption Statistics for Hybrid Systems.

The average solar energy output of the hybrid system is 500 kW, with a standard variation of 120 kW. Although the average amount of solar energy produced is rather high, there is significant variation in its output over time, as seen by the production ranging from a minimum of 300 kW to a maximum of 700 kW. The average output of wind energy is 350 kW, and the standard deviation is 100 kW. A range of 200 kW to 600 kW of wind energy output shows that while there is not as much variation as with solar energy, there is still some significant variation in the output. The entire energy output, which combines both solar and wind energy, averages 850 kW with a standard variation of 150 kW. The range of overall energy output, which is significantly variable between 500 kW and 1300 kW, shows that the hybrid system might produce a wide range of energy levels depending on system performance and environmental factors. The mean of the average energy consumption is 700 kWh with a standard deviation of 180 kWh. Within the range of 400 to 1100 kWh, there are changes in consumption which may have changed due to altered demands or changes in system operation variables.

Table 2 below indicates a comparison of the predicted versus the actual energy output of a wind and solar hybrid system at various times of the day. It also shows % error between projected and actual energy output to judge the accuracy of the system's energy forecasts.

Table 2: Hourly Prediction vs. Real Energy Production (Wind + Solar Hybrid).

Hour	Forecast Output (kWh)	Actual Output (kWh)	Error (%)
00:00	60	62	3.33
06:00	120	118	1.67
12:00	400	380	5.00
18:00	350	360	2.86
24:00	70	72	2.86

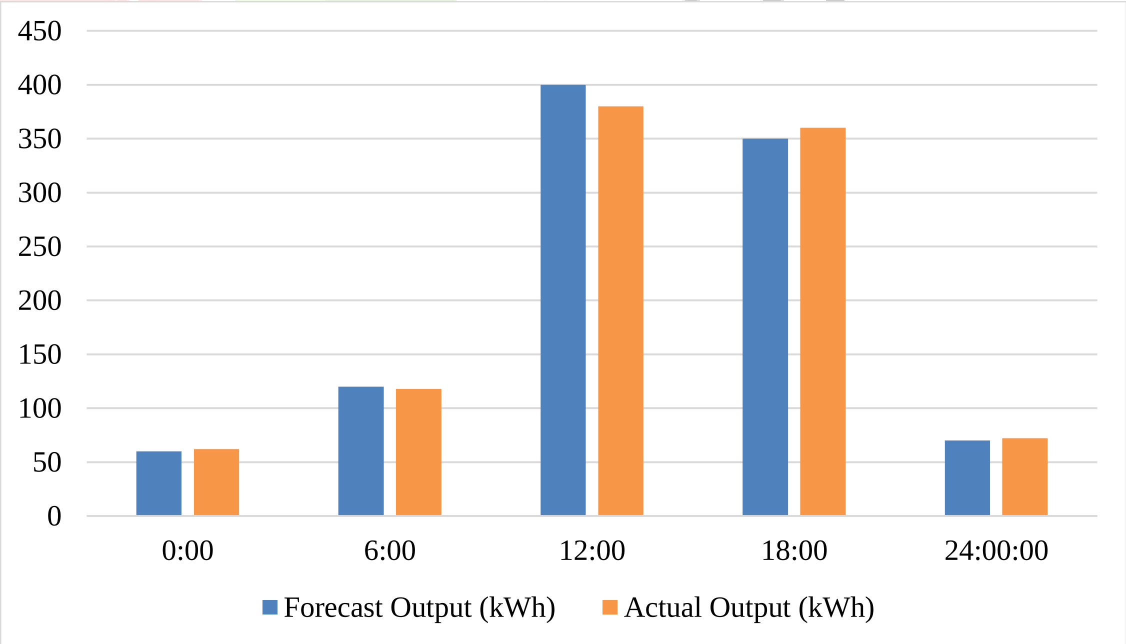

Figure 2: Graphical representation of Hourly Prediction vs. Real Energy Production (Wind + Solar Hybrid).

There was a very small error of 3.33% at 00:00 between the forecasted and actual outputs, which were 60 kWh and 62 kWh, respectively. This indicates that the prognosis is quite accurate for the midnight hour. The error in the forecast was very small, 1.67%, while the forecasted output was 120 kWh at 06:00, close to the actual output of 118 kWh. This is also good accuracy for the morning. With a predicted output of 400 kWh and actual output of 380 kWh, there was greater disparity at 12:00, giving a result of an inaccuracy of 5.00%, indicating that there is a variation in the mid-day forecast. The output at 18:00, which was 350 kWh as predicted, occurred at 360 kWh in terms of actual output. This shows a lesser inaccuracy of 2.86%, hence proving to be an excellent forecast for the evening. Last but not least, another evidence of exact nighttime forecasting was given at 24:00, when the output as predicted was 70 kWh, and the actual output taken has been 72 kWh, which has only a minor error of 2.86%. With minor errors at each of the observed hours, the predictions of the system are generally quite accurate.

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IV. CONCULSION

V. The hybrid renewable energy system functions properly, and there is relatively low fluctuation in the yields of wind and solar energy as supported by the energy production analysis and accuracy in forecasting. There are low percentages of mistakes during various periods of the day with the majority being less than 5%, showing the high precision of the model for forecasting. This indicates that the system is capable of very accurate energy generation prediction, maximizing the integration of wind and solar power. When applied to such hybrid systems, machine learning models can significantly enhance the dependability and effectiveness of renewable energy management, helping in shifting to a more sustainable energy future, as stated by the overall performance and forecasting consistency.

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