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APPLICATION OF NEURAL NETWORKS FOR PREDICTING ENERGY PRODUCTION FROM HYBRID POWER SYSTEMS CONSIDERING THE INFLUENCE OF STOHASTIC WEATHER CHANGES

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Abstract: This paper investigates the potential application of neural networks for predicting electricity production in hybrid systems combining photovoltaic (PV) panels and wind turbines. The research focuses on identifying key factors affecting the efficiency and reliability of these systems, including weather variability, PV panel temperature control, solar irradiation, and panel contamination by dust and other pollutants. Artificial neural network (ANN) models are used to predict power output, incorporating robust data filtering and parameter optimization techniques. Through case studies from Germany, the significant role of stochastic weather patterns on energy production is demonstrated, highlighting the need for accurate modeling and strategic management. The findings emphasize that accurate modeling and prediction are crucial for optimizing the operation and reliability of hybrid systems, facilitating a reduced dependency on fossil fuels and promoting sustainable power accessibility in remote areas. By applying a Feed Forward Back Propagation Network (FFBPN), this research demonstrates improved prediction accuracy of power outputs, which is crucial for effective integration and management of renewable sources in the power grid. The study supports ongoing refinement of predictive models and system integration strategies to fully harness the potential of hybrid renewable energy systems.

Keywords: hybrid power plant, neural network, machine learning, renewable sources, solar power plant, wind farm

INTRODUCTION

The integration of renewable energy sources, such as solar photovoltaic (PV) and wind energy, is essential to addressing the global energy and environmental challenges. The shift from fossil fuels to renewable energies aims to reduce greenhouse gas (GHG) emissions and limit the global average temperature increase to below 2°C [1]. Renewable energy sources, particularly solar and wind, are considered essential for future low-carbon emission scenarios due to their high energy return on investment and minimal operational GHG emissions.

Hybrid power systems, which combine PV panels and wind turbines, offer a promising solution for sustainable energy production. These systems leverage the complementary nature of solar and wind resources, ensuring a more reliable and efficient energy output. However, the intermittent nature of these resources and the stochastic weather patterns pose significant challenges to accurate energy production prediction and grid stability [2].

Neural networks have emerged as a valuable tool for predicting energy production in hybrid systems, accounting for various factors such as weather variability, solar irradiation, and temperature control of PV panels. By employing robust data filtering and parameter optimization techniques, neural network models can enhance the accuracy of power output predictions. This is crucial for the effective integration and management of renewable energy sources in the power grid [3].

Furthermore, the systematic review on the photovoltaic and wind energy potential in Europe emphasizes the need for precise and region-specific assessments, accounting for geographical, technical, and economic variations. These insights are essential when developing neural network models to predict energy production from hybrid systems, as the variability in energy potential due to stochastic weather changes must be accurately captured and integrated into predictive algorithms [2]. Additionally, the variability highlighted in the systematic review will inform the development of robust neural network models capable of adapting to diverse and changing weather patterns, thereby improving the reliability and sustainability of hybrid energy production.

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This paper focuses on the application of artificial neural networks (ANN) for predicting electricity production in hybrid power systems under stochastic weather conditions. The research aims to identify key factors affecting the efficiency and reliability of these systems and demonstrate the role of neural networks in optimizing their operation. The research leverages advanced neural network architectures to model the non-linear relationships between weather variables and energy output, aiming to improve the predictability and stability of renewable energy contributions to the grid. Case studies from Germany highlight the significant impact of weather variability on energy production and underscore the need for accurate modeling and strategic management of hybrid power systems [4].

By integrating neural networks into the forecasting process, it can enhance the management of hybrid power systems, ensuring a more resilient and efficient energy supply. This approach not only addresses the inherent uncertainties in weather patterns but also supports the transition towards a more sustainable and renewable energy future. The findings of this research are expected to contribute significantly to the development of more sophisticated and adaptive forecasting models, ultimately facilitating the broader adoption of renewable energy technologies.

1. THE INTERMITTENT NATURE OF WIND AND PV GENERATION

Integrating wind and photovoltaic (PV) generation into the power grid poses challenges due to their intermittent nature, which directly affects the predictability and stability of electricity production in hybrid power systems.

1.1. The influence of the wind speed

Hybrid power systems represent units for energy production that convert primary energy sources into electrical energy. They utilize wind and solar energy for electricity generation and can vary in size, from small residential installations to large industrial facilities. They consist of wind turbines, solar panels, and energy storage systems (batteries). There is a significant difference between small hybrid systems and large hybrid systems. The biggest difference lies in the height of the wind turbine tower. In Germany, the average height of wind turbine towers is 100m [5], while in the Netherlands, it is 40-50m [6]. At these heights, wind speeds and behaviours differ from those on the ground. The kinetic energy of the wind depends on the measurement height. Beyond the crossover height, the average daytime wind speed is less than the average night time wind speed, whereas the situation is reversed below the crossover height [5]–[9]. This further implies that the energy production from PV panels is, on average, negatively correlated with wind production at those heights, indicating that this is the optimal height for placing wind turbines. Energy production from PV panels largely depends on the geographical latitude they are installed on, the number of sunny hours per year, and temperature. Increasing temperature and overheating of the panels negatively affect their operation. Additionally, contamination due to increased levels of dust in the atmosphere or the occurrence of fog/smog at night leaves deposits on the panel and reduces their production. Wind energy production mainly depends on the geographic location and can be predicted based on terrain data and meteorological conditions in a specific area. If production is observed over a shorter period, the influence of the stochastic nature of the wind increases, but over a longer period, these stochastic effects decrease [10].

1.2. The influence of the angle of solar rays

The movement of the sun can be approximated, and solar trackers can even be used to eliminate these effects. Impurities accumulating on the panels can be removed and kept under control through regular maintenance. The impact of external factors on PV panels, such as temperature and specific system conditions, does not significantly affect production forecasting. However, it is almost impossible to predict the movement of clouds, which can significantly disrupt energy production, as their movement and appearance are entirely stochastic processes [8] - [9]. Integrating large hybrid systems into the power grid will cause certain management problems, due to their intermittent and nondispatchable nature [11]. The inability to accurately predict production from hybrid systems poses a serious challenge for system operators. Production largely depends on external weather conditions, which can significantly affect the stability of the power system. Increased integration of hybrid systems into the power system leads to a change in the system's inertia, in a way that when hybrid systems replace conventional generators, the inertia of the energy system will decrease, resulting in lower minimum values of the boundary frequency and faster frequency rise due to disturbances [12]. Figure 1 ilustrates the concept of a hybrid power plant.

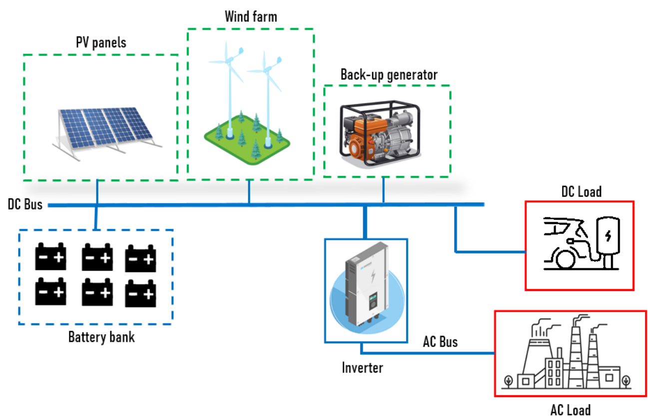

Figure 1: Hybrid Power Plant

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The schematic diagram of the hybrid power system integrates multiple energy sources and components to ensure reliable power supply. It includes photovoltaic (PV) panels, a wind farm, a backup generator, a battery bank, an inverter, and different types of loads. The PV panels and wind farm generate direct current (DC) electricity, which flows into the central DC Bus. The backup generator provides supplementary DC power when renewable sources are insufficient. The battery bank stores excess DC electricity generated by the PV panels and wind farm for later use. The DC Bus distributes this electricity to various parts of the system, including an inverter that converts DC electricity into alternating current (AC) electricity for AC loads. The AC Bus then distributes the AC electricity to devices and systems requiring AC power, while the DC Bus also directly supplies DC loads such as electric vehicle chargers. This configuration ensures efficient integration and utilization of renewable energy sources, storage, and backup power, meeting the demands of both DC and AC loads.

1.3. Influence of Atmospheric Pressure and Temperature Changes on Wind Speed and Solar Energy Production

Wind speed depends on atmospheric pressure. A wind turbine generates electrical energy as a function of wind speed, depending on the surface area covered by the wind turbine blades. If the difference in atmospheric pressure is greater, higher wind speeds occur [13]. When discussing wind speeds at the heights where wind turbines are located, wind behavior is harder to predict due to more pronounced temperature changes that affect wind speeds. Because of these circumstances, there are changes in the meteorological aspect of predicting wind speeds throughout the day, month, and year. Due to these fluctuations, wind behavior is described in the frequency domain [14]. Energy production from photovoltaics (PV) is a function of the wave-length of light reaching the solar panels [15]. Energy is produced based on the photoelectric effect. In addition to the dependence on the wavelength of light, production also depends on panel heating. Figure 2. shows the electrictiy production of a photovoltaic panel during winter and summer seasons located in Sarajevo. It highlights the variation in power output due to seasonal changes, with lower production in winter and higher in summer. It shows that difference in electricity production from each panel can vary by up to 50% depending on the season.

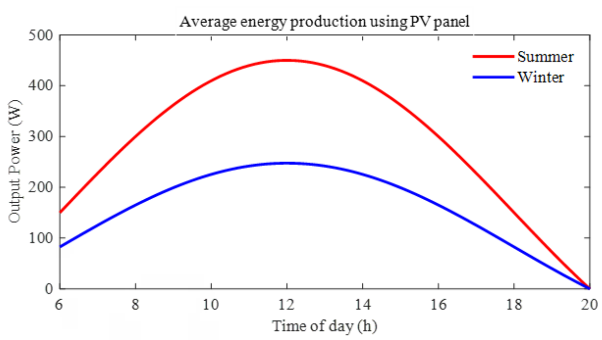

Figure 2: Average Production of Electrical Energy using PV Panel with different seasons conditions

The summer curve shows higher energy production, nearly double the winter peak, reflecting the seasonal variation in sunlight intensity and duration. Both curves display a symmetrical pattern around noon, indicating a consistent increase in power output as the sun rises and a decrease as it sets. The longer duration of daylight in summer is evident as the red curve starts earlier and ends later than the blue curve. This graph effectively highlights the significant impact of seasonal changes on solar energy production, with the PV panel generating more energy during summer compared to winter.

Wind energy and solar energy change nonlinearly. Although clouds obstruct sunlight from reaching solar panels, they can lead to cooling of excessively heated panels, so they can sometimes be beneficial in that regard. Considering the above, it can be concluded that most assumptions in hybrid systems are of a deterministic nature. It is impossible to completely predict events in the future.

In other words, it is impossible to completely accurately predict the production of electrical energy from renewable sources. No matter how many factors are taken into account, they change at certain intervals, and there is always a certain statistical uncertainty in predicting production from solar panels and wind turbines [15].

2. NEURAL NETWORK MODELING AND VALIDATION

By leveraging artificial neural network techniques, the aim is to harness the complex relationships between various environmental factors and energy output. This chapter provides a comprehensive overview of the methodologies used to gather and preprocess input data, design and train neural network architectures, and rigorously validate the models to ensure their reliability and accuracy. When modeling neural networks, it is necessary to go through certain steps. Relevant data related to energy production using wind turbines and PV panels must be collected [17] – [19]. After collecting the input data, it is necessary to perform filtering and remove data that is redundant or deviates significantly from the other data. This process is carried out to prevent data with large deviations from influencing the accuracy of the results provided by the neural network.

2.1. Input factors used for training neural networks

When selecting a location for the construction of a hybrid power system, it is necessary to consider data such as wind speed and the number of sunny days at a particular location. In other words, the behavior of temperature, air pressure, and relative humidity is taken into account, and based on this data, predictions of wind speed and solar radiation are made. Temperature affects the energy reaching the solar panels and the behavior of the wind, including its direction and intensity. Air pressure, which varies with altitude, affects the operating condition of the system. If the hybrid power plant (HPP) is built at higher altitudes, the pressure is lower. Changes in pressure lead to changes in the operating conditions of the HPP. Specifically, there is an increase in pressure during dry weather conditions, while pressure decreases during cloudy weather. Humidity, calculated using the ideal gas equation with certain modifications, indicates the presence of water particles in the atmosphere. An increase in humidity means that there is a greater number of water particles in the atmosphere [16]. Figure 3. shows neural network architecture.

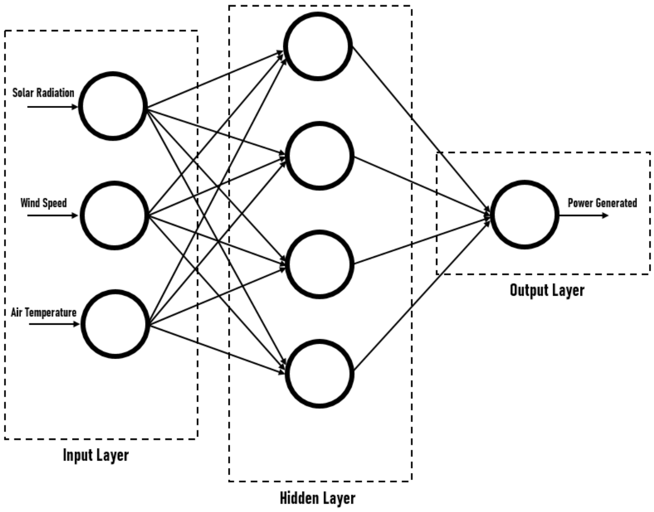

Figure 3: Neural network architecture

2.2. Modeling Neural Networks

The network architecture includes an input layer, hidden layers, and an output layer. The input layer receives data such as weather conditions and system parameters. Hidden layers perform complex transformations on the input data, allowing the network to learn patterns and relationships. The output layer produces the final prediction of electricity production. As the activation function, the sigmoid function was chosen. The sigmoid function is particularly useful in capturing non-linear relationships in the data, which is common in energy production systems. The learning algorithm used for training neural networks is backpropagation. It adjusts the weights of connections between neurons to minimize the difference between the actual output and the predicted output.

It is necessary to select parameters that directly and significantly affect energy production to save computational resources. The choice of using only air temperature, solar radiation, and wind speed as input parameters is based on their significant influence on energy production in hybrid power systems. These parameters are crucial for determining the potential energy output from both solar panels and wind turbines. The selection of these parameters is also influenced by their availability and ease of measurement, as they are commonly monitored in renewable energy systems. Including additional parameters would increase the complexity of the model and require more data. After the input data is selected and filtered, the neural network training begins using an appropriate algorithm [18]. Training is conducted until results with a certain level of accuracy are achieved. In this case, the installed wind turbines have a power capacity of 700 kW, while the PV panels have a capacity of 1000 kW. The prediction is made for the entire hybrid power plant, considering the overall energy production from all the panels and turbines in the system.

2.3. Validation of ANN

The validation procedure for the neural network model was crucial to ensure its accuracy and reliability. Several procedures were taken to prevent overfitting and underfitting, including using a validation dataset separate from the training dataset. This dataset was not used during the training process and served to evaluate the model's performance on unseen data. Additionally, techniques such as early stopping and regularization were employed. Early stopping involved monitoring the model's performance on the validation dataset during training and stopping the training process when the performance stopped improving, thus preventing overfitting. Regularization techniques, such as L1 and L2 regularization, were used to add penalty terms to the loss function, discouraging the model from fitting the training data too closely and improving its generalization ability. The validation procedure involved splitting the dataset into training, validation, and test sets. The training set was used to train the model, the validation set was used to tune hyperparameters and prevent overfitting, and the test set was used to evaluate the final performance of the model. To achieve greater accuracy, input data from a larger number of installed hybrid power systems are considered. From the theory of statistics, the correlation between two dependent variables can be calculated as

$$\rho_{X,Y} = \frac{E\left[(X-\overline{X})(Y-\overline{Y})\right]}{\sigma_X \sigma_Y} \tag{1}$$

Here, σ_X and σ_Y represent the standard deviations of variables X and Y, respectively.

In this study, the Feed Forward Back Propagation Network (FFBPN) approach is utilized. Where $w_{i,j}$ represents the weight coefficient and x_j is the variable's initial value, and x_i is its new value.

$$x_i = \sum_{j=1}^{n} w_{i,j} x_j \quad (2)$$

The variance can be calculated as:

$$\sigma_{x_i}{}^2 = \sum_{X=1}^{N}\sum_{Y=1}^{N} w_X w_Y \sigma_X \sigma_Y \rho_{X,Y} \quad (3)$$

Based on a certain variance, data filtering can be performed, which is necessary to increase the accuracy of the output data. Between the input and hidden layers, an sigmoid activation function is used, which returns a value without affecting the weighted sum of the input.

$$f(x) = \frac{1}{1+e^{-x}} \quad (4)$$

After obtaining the results, it is necessary to verify these results to ensure that the neural networks are reliable for future use. Once the aforementioned procedures are completed, the model can predict wind and solar energy production for a given input dataset dependent on weather conditions, and hybrid system production becomes more manageable [20]. The estimated values are compared with the measured values through correlation and error analysis. Mean Bias Error (MBE), Normalized Root Mean Square Error (*NRMSE*) and Correlation Coefficient (R) are used for this purpose.

$$NRMSE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2}}{y_{\max} - y_{\min}} \quad (5)$$

$$R = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 (y_i - \bar{y})^2}} \quad (6)$$

$$IA = 1 - \frac{\sum_{i=1}^{N}(x_i - y_i)^2}{\sum_{i=1}^{N}\left(\left|x_i - \bar{x}\right| + \left|y_i - \bar{y}\right|\right)^2} \quad (7)$$

where N represents the number of observations, y_i represents the estimated value, and x_i represents the measured value [21].

3. RESULTS OF ANN PREDICTION

The results of the ANN model's predictions for electricity production in hybrid power systems are detailed in this chapter. The effectiveness of the model is evaluated based on its accuracy in forecasting power output under varying meteorological conditions. The performance metrics used to assess the model's accuracy provide insights into its reliability for practical applications.

3.1. Data used for Artificial Neural Network Training

Neural network training is conducted using a dataset of solar and wind power production in the area of Germany [22]. The dataset used in this study was gathered over a period of 100 days, during which the production of the hybrid power plant was continuously monitored. Parameters such as temperature, pressure, and wind speed were measured hourly. The prediction is based on the neural network's learned patterns from the training dataset and is not performed on the same datased used for training. The data used covers the period from August 15, 2023, to November 23, 2023, corresponding to a time span of 100 days. Figure 4. shows the average daily power output of the hybrid power plant. Due to lower wind speeds and fewer sunny hours, the output power was lower. Under ideal conditions, the power plant can achieve its installed capacity. Considering the changes in meteorological instances, a decline in electricity production is noticeable after 35 days, which occurs due to reduced solar radiation and decreased output of PV panels. The difference in electricity production from each panel can vary by up to 50% depending on the season, i.e., depending on the emitted solar radiation. Occasional fluctuations in electricity production occur due to changes in weather conditions and the occurrence of sunny days or higher-than-average wind speeds. Due to sudden changes in meteorological conditions, deviations in electricity production prediction occur. When the trend of meteorological condition changes is constant, actual production results align with prediction results.

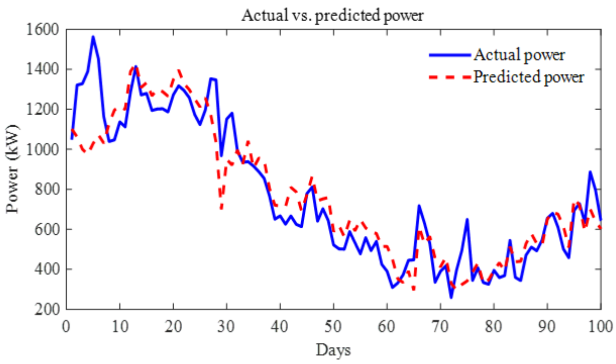

Figure 4: Results after using Artificial Neural Network for predicting Power Output from Hybrid Power Plant

Figure 4 illustrates the performance of an artificial neural network (ANN) model in predicting the power output of a hybrid power plant over a period of 100 days. The x-axis represents the days, while the y-axis shows the power output in kilowatts (kW). The blue solid line indicates the actual power output measured from the hybrid power plant, and the red dashed line represents the predicted power output generated by the ANN model. The graph reveals that the ANN model closely follows the actual power output trends, capturing the fluctuations and seasonal variations effectively. Although there are minor deviations between the actual and predicted values, the overall alignment demonstrates the model's capability to accurately forecast power output. This performance validation is crucial for optimizing the operation and management of hybrid power systems, ensuring reliability and efficiency in energy production during stochastic weather changes.

3.2. Statistical Analysis of Data

Table I shows the statistical analysis of data after using an artificial neural network to predict power output in hybrid power systems. The analysis includes the Index of Agreement, Normalized Root Mean Square Error, and Correlation Coefficient, which are key metrics for evaluating the accuracy and reliability of the ANN model.

Table I: Statistical Analysis of Data after using Artificial Neural Network for predicting Power Output

Index of Agreement	0.8453
Normalized Root Mean Square Error	0.3620
Correlation Coefficient	0.9205

The $NRMSE$ for the tested case is 0.3620, indicating a satisfactory level of accuracy in the model's predictions. Furthermore, the high correlation coefficient of 0.9205 demonstrates a robust relationship between the predicted and observed values, supporting the practical utility of the proposed model. These findings align with existing literature, providing additional validation for the efficacy of the developed model.

4. CONCLUSION

The integration of renewable energy sources, particularly wind and solar, into the power sector is vital for achieving sustainability and reducing reliance on fossil fuels. Hybrid power systems combining these sources offer a promising solution, but they face challenges related to weather variability and system optimization.

This research has highlighted the importance of temperature regulation for solar panels, as well as the impact of wind speed, solar radiation, and panel contamination on overall system performance. Neural networks have emerged as a valuable tool for modeling and predicting energy production, enabling better management of hybrid power systems. Neural networks were utilized for modeling and predicting energy production based on weather conditions, emphasizing data filtering and parameter selection.

Case studies from Germany underscored the significance of accurate forecasting and management strategies in maximizing energy production and ensuring grid stability. Moving forward, further research and development efforts should focus on refining modeling techniques, enhancing system integration, and advancing energy storage technologies to unlock the full potential of hybrid power systems in the transition to a sustainable energy future. Implementing the proposed strategies to enhance these systems efficiency and reliability could significantly reduce greenhouse gas emissions and ensure energy security in remote areas. For future research, further investigation into precise meteorological forecasting and management of hybrid energy systems is recommended to advance their performance and sustainability.

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BIOGRAPHY

Adin Memić was born in Sarajevo, Bosnia and Herzegovina. He is the B.Sc. student at the Faculty of Electrical Engineering, University of Sarajevo, Department for Electric Power Engineering. His research interests are in renewable energy sources, power system analysis and artificial intelligence.

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Medina Kapo was born in Sarajevo, Bosnia and Herzegovina. She received her B.Sc. and M.Sc. degrees in computer science and informatics from the Faculty of Electrical Engineering, University of Sarajevo (Bosnia and Herzegovina), in 2021 and 2023, respectively, where she is currently pursuing the Ph.D. degree. From 2023 she has been with the same faculty as a teaching assistant. Her research interests are in artificial intelligence, data science, databases, image processing.