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RESEARCH ARTICLE | **RENEWABLE ENERGY**

Evaluation and Prediction Performance of Solar Panel and Wind Turbine Systems Using Simulation

Sharaf Aldeen Alfathi[1], Guzlan Miskeen[2], Wajdi Mohammed Mremi[3]

[1]Electrical and Electronic Engineering, Faculty of Engineering, Wadi Alshatti University, Brack – Libya
[2]Medical Engineering, Faculty of Engineering, Wadi Alshatti University, Brack – Libya
[3]Electrical and Electronic Engineering, Faculty of Engineering, Wadi Alshatti University, Brack – Libya

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ABSTRACT

Renewable energy is one of the important sustainable energy sources due to its low carbon emissions compared to fossil fuels; however, its performance is affected by climatic conditions. This study aims to evaluate and predict the performance of photovoltaic (PV) systems and wind turbines in Libya through two phases. In the first phase, MATLAB/Simulink was used to model and simulate three PV technologies monocrystalline, polycrystalline, and amorphous and to analyze the effects of solar irradiance and temperature on their performance. The results indicate that monocrystalline modules are more responsive to increased irradiance, while amorphous modules are less sensitive to temperature rise. Wind energy systems were analyzed by comparing two horizontal-axis wind turbines, Gamesa and Acciona, under different wind speeds, where the Gamesa turbine showed superior performance at high speeds. In the second phase, an artificial neural network trained using synthetically generated data achieved high prediction accuracy for both energy systems.

التقييم والتنبؤ بالأداء لنظامي الألواح الشمسية وتوربينات الرياح بإستخدام المحاكاة

شرف الدين الفتحي [1]، غزلان بن مسكين [2]، وجدي محمد مريمي [3]

الملخص

تُعد الطاقة المتجددة أهم مصادر الطاقة المستدامة نظرًا لانخفاض انبعاثاتها الكربونية مقارنة بالوقود الأحفوري، إلا أن أداء أنظمتها يتأثر بالظروف المناخية. تهدف هذه الدراسة التقييم والتنبؤ بأداء نظامي الألواح الشمسية وتوربينات الرياح في ليبيا عبر مرحلتين. في المرحلة الأولى، استخدم MATLAB/Simulink لنمذجة ومحاكاة ثلاثة أنواع من الألواح الشمسية، وهي أحادي البلور، متعدد البلورات، وغير المتبلور، ودراسة مدى تأثير الإشعاع الشمسي و الحرارة على أدائها. أظهرت النتائج أن اللوح الأحادي أكثر استجابة لارتفاع الإشعاع، بينما كان اللوح غير المتبلور الأقل تأثرًا بارتفاع الحرارة. تمت محاكاة توربينات الرياح ومقارنة أداء نوعين من التوربينات ذات المحور الأفقي، وهما Gamesa وAcciona، من خلال دراسة مدى تأثير سرعة الرياح، حيث تفوق توربين Gamesa عند السرعات العالية. في المرحلة الثانية، تم توظيف شبكة عصبية اصطناعية مدربة باستخدام بيانات مولدة اصطناعيًا، وحققت دقة تنبؤ مرتفعة بمعامل تحديد بلغ 0.98 ودقة 96% للألواح الشمسية و0.99 ودقة 99% لتوربينات الرياح، مما يؤكد فعالية الشبكة العصبية في التنبؤ بالأداء للنظامين.

الكلمات المفتاحية

الطاقة المتجددة
الألواح الشمسية
توربينات الرياح
ماتلاب/سيمولينك
بايثون
الشبكة العصبية الإصطناعية

Introduction

Renewable energy is a sustainable and environmentally friendly source due to its lower emissions compared to fossil fuels [1]. Population growth, along with industrial and technological development, has increased the demand for electricity, while most power generation still relies on fossil fuels, leading to various environmental challenges. It is expected that global electricity consumption will double over the next two decades as a result of rapid population growth and continuous technological advancement, placing additional pressure on conventional energy systems. Consequently, reliance on renewable energy sources such as solar and wind has increased, as they offer high sustainability, environmental compatibility, and widespread global adoption, and they represent the main focus of this study [2, 3]. However, the performance of renewable energy systems is affected by climatic variations, making it difficult to achieve optimal performance and leading to reduced productivity [4].

The global renewable energy market has experienced significant growth in recent years, driven by increasing concerns over climate change and global warming, along with international policies supporting the transition toward a green economy. By the end of 2024, global renewable energy

*Corresponding author
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capacity reached approximately 4.45 TW, led primarily by solar and wind energy, reflecting the rapid worldwide shift toward clean and sustainable power sources [5]. By the end of 2024, the global installed capacity of renewable energy sources reached approximately 4,448 GW, including solar energy, wind energy, hydropower, geothermal energy, marine energy, and bioenergy [6]. Solar photovoltaic energy accounted for the largest share, with an installed capacity of around 2,200 GW, followed by wind energy with a capacity exceeding 1,021 GW. This trend reflects the accelerated global shift toward adopting sustainable energy technologies to meet the growing demand for electricity while reducing carbon emissions [7].

Renewable Energy in Libya

Libya has significant potential in renewable energy, particularly solar and wind, yet it still relies on fossil fuels for about 99% of its electricity generation, making the power sector the largest contributor to CO_2 emissions at 36%. The national strategy for 2020–2050 aims to increase the share of renewable energy to 30% by 2030 and surpass fossil energy sources by 2050 [8]. Libya also benefits from high solar irradiance exceeding 2500 kWh/m² annually and more than 3500 sunshine hours per year, in addition to strong wind speeds reaching around 8 m/s in coastal and mountainous areas, making it a promising environment for clean energy development [9].

Solar and Wind Energy

Solar energy is considered one of the cleanest and most abundant renewable energy sources in the world, owing to its sustainability [10]. environmental friendliness, and ease of use, which has contributed to its widespread adoption and large-scale utilization [11]. Solar panels rely on photovoltaic cells as the fundamental units that directly convert solar radiation into electric [4, 12]. In this context, the use of solar energy for oasis lighting as an alternative to conventional lighting systems represents a sustainable solution that reduces fossil fuel consumption and carbon emissions, while enhancing reliance on clean energy sources, particularly in remote areas [13].Wind energy is also among the most efficient renewable sources, where the movement of air is utilized to generate electricity through turbines [14]. The performance of these turbines is influenced by wind characteristics such as variations in speed across locations and times, as well as aerodynamic turbulence. Moreover, the average wind speed is an important indicator linked to seasonal climatic conditions and changing weather systems [15, 16].

Mathematical Modeling

Mathematical modeling is essential for simulating systems and analyzing the processes and influencing factors within them, as system characteristics are translated into a computational model used for simulation [17]. Although ready-made software tools such as SAM [18], HOMER [19], and PVsyst [20] are available for studying renewable energy systems, their capabilities in analyzing and modeling electrical circuits remain limited.

MATLAB/Simulink

In this research, the first stage focuses on evaluating the performance of photovoltaic panels and wind turbines using simulation techniques. MATLAB/Simulink is employed due to its flexible and visually intuitive environment for analyzing electrical and electronic circuits, in addition to its built-in models that facilitate the modeling process. This platform is widely used in research and application for simulating electromechanical and energy systems [21].

Artificial neural network (ANN)

The second stage involves performance prediction for both systems using artificial intelligence methods—specifically artificial neural networks (ANN) by analyzing datasets that incorporate both climatic and electrical variables. This approach supports the development of intelligent models capable of enhancing prediction accuracy and aiding decision-making in renewable-energy applications [21].

In recent years, substantial attention has been directed toward modeling solar and wind energy systems, with approaches ranging from mathematical formulations and software-based simulations to the integration of artificial intelligence techniques. Locally, numerous studies have confirmed the economic, technical, and environmental feasibility of using solar and wind energy**,** whether individually or in combination through hybrid systems**,** integrated with energy storage systems such as batteries or pumped hydro storage (PHS) plants**.** Table (1) summarizes the most influential studies in this field.Karakilic et al. employed the PSIM platform to simulate the performance of three 100W photovoltaic module types, demonstrating that monocrystalline panels are the most sensitive to temperature variations and that lower temperatures combined with higher irradiance significantly enhance energy output; however, their work did not incorporate AI-based prediction under variable operating conditions [12]. Building on this, Nfaoui et al. developed a single-diode model for polycrystalline modules that integrates irradiance, temperature, and wind speed, achieving strong agreement with PVsyst simulations and emphasizing the importance of accounting for wind speed in performance estimation [4]. In a related study, Alsharif et al. investigated the impact of atmospheric dust accumulation on the performance of photovoltaic panels in Libya using MATLAB/Simulink supported by experimental measurements. The findings revealed a significant reduction in cell efficiency as dust levels increased, highlighting the critical role of regular cleaning and maintenance in preserving system performance and maximizing energy output [22]. Mohammad et al. further advanced solar power prediction by applying linear regression (LR) and simple linear regression (SLR), achieving high accuracy with R^2 values reaching 100% and remarkably low MAPE values of 0.7% and 0.45%, using real datasets collected at different tilt angles [23]. In the wind-energy domain, Suresh et al. modeled a wind turbine in MATLAB/Simulink, analyzing the influence of blade length, wind speed, and air density, and evaluated system performance using the power coefficient and pitch angle, without adopting AI-based predictive methods [24]. Malakar et al. designed a 1-MW grid-connected wind turbine using superconducting generators and advanced control strategies, achieving an effective power output of 0.96 MW and reactive power of –0.22 MVAR, with efficiency improvements attributed to the integration of a capacitor bank [25].Interest has expanded to the spatial and economic assessment of wind energy. Salem et al. analyzed wind potential in the Al-Jabal Al-Gharbi region using commercial turbine simulations and reported strong economic feasibility, with a minimum levelized cost of energy of about 3.4 ¢/kWh in Nalut and Yafran using a 3.3 MW SUZLON turbine, alongside a reduction of approximately 4.4 tons of CO_2 per year per megawatt, supporting carbon neutrality [26].Abdelsattar et al. compared various machine-learning algorithms including LR, SVR, RF, AdaBoost, LightGBM, CatBoost, XGBoost, and ET with deep-learning models such as ANN, RNN, CNN, and LSTM for wind-power forecasting using R^2, MAE, and RMSE as metrics. Their findings showed that the Extremely Randomized Trees (ET) model achieved the highest accuracy among ML methods (72.3%), while ANN performed best among deep-learning models (72.5%), underscoring the critical role of preprocessing in predictive performance [27]. In another study, Ahmed et al. assessed the solar and wind energy potential in Libya using the System Advisor Model (SAM) across 12 locations based on long-term SolarGis data. The findings indicated that these technologies can meet a substantial portion of electricity demand, achieving annual CO_2 emission reductions of about 3.82 million tons and economic savings of approximately USD 286.3 million from a 1000 MW renewable power plant operating at a 40% capacity factor [28].Similarly, Aqila et al. examined hybrid renewable energy systems for residential applications, proposing a new design and analysis methodology based on actual appliance power ratings and operating schedules. Using real climatic and load data from a house in Samno–Sebha and SAM-based simulations, the study demonstrated that the proposed system can reliably meet electricity demand while delivering economic and environmental benefits through lower energy costs and the export of surplus power to the grid [29]. Furthermore.Chahal et al. employed machine learning and deep learning techniques to predict power-grid stability using multiple models such as LR, NB, DT, SVM, RF, XGBoost, KNN, and an ANN optimized with the Adam algorithm. Their results showed that the ANN model outperformed the others, achieving an accuracy of 97.27%, a precision of 96.79%, a recall of 95.67%, and an F1- score of 96.22%, supported by data augmentation and feature scaling [30]. Despite the substantial body of research addressing solar and wind energy systems, only a limited number of studies have introduced an integrated framework that combines simulation modeling with artificial intelligence to evaluate each system independently. This study adopts such a framework by developing simulation models in MATLAB/Simulink to analyze the operational behavior of photovoltaic panels and wind turbines, followed by the application of artificial neural networks (ANN) in Python to forecast their performance. This approach strengthens model reliability and enhances predictive accuracy by examining system efficiency and performance indicators under varying operating conditions, ultimately providing a practical methodology for improving the operational effectiveness of both solar and wind systems.

Methodology

The methodology of this study is organized into two principal phases. In the first phase, MATLAB/Simulink was employed to model and simulate both Solar panels and wind turbines for performance assessment. The solar panels were modeled based on the electrical equivalent circuit of the solar cell., providing flexibility in parameter adjustment and enabling the examination of the effects of solar irradiance and temperature. In contrast, wind turbines were modeled using built-in Simulink models due to the lack of scientific references describing an equivalent electrical circuit and to avoid unnecessary mathematical and dynamic complexity. This phase also involved analysing the influence of wind

Table 1: summarizes previous studies on energy and emissions management in data centers

Ref.	**Algorithms Used**	**Tool/ Environment**	**Main Objective**	**Key Findings**
[12]	No algorithms used	Power Simulation	Analyzing the performance of solar panels under the influence of temperature and irradiance	monocrystallin panels showed higher cooling frequency
[4]	No algorithms used	MATLAB/Simulink + PVSyst	Developing a Model to Analyze the Impact of Climatic Factors	The model was significantly influenced by both solar irradiance and temperature
[22]	No algorithms used	MATLAB/Simulink	Assessing dust impact on PV performance	Dust accumulation reduced PV efficiency, emphasizing regular cleaning
[23]	SLR-LR	MATLAB/Simulink	Predicting Solar Power Generation Using Machine Learning Techniques	The SLR algorithm outperformed
[24]	No algorithms used	MATLAB /Simulink	Evaluating and analyzing wind-turbine performance	The model performed well under high wind-speed conditions
[25]	No algorithms used	MATLAB/Simulink	Designing a 1-MW wind-turbine system	The model maintained stable output with effective efficiency compensation
[26]	No algorithms used	System Advisor Model	Wind energy potential assessment and turbine selection	Achieves low LCOE (~3.4 ¢/kWh), proving economic feasibility and CO_2 reduction
[27]	LR, SVR, RF, XGBoost, LSTM, ET, ANN, RNN, CNN	Jupyter Notebook/ Python	Comparing machine-learning and deep-learning algorithms for predicting solar and wind power	Deep-learning algorithms, particularly ANN, offered superior predictive accuracy
[28]	No algorithms used	System Advisor Model	Evaluation of PV, CSP, and wind technologies in Libya	Renewables meet high demand, cutting ~3.82 Mt CO_2 with strong economic savings
[29]	No algorithms used	System Advisor Model + Excel	Hybrid system design & evaluation	Meets demand, exports surplus, and achieves low LCOE, proving feasibility
[30]	No algorithms used	Jupyter Notebook / Python	Predicting renewable-energy output using machine-learning algorithms	ANN models outperformed other algorithms in prediction accuracy

speed on turbine performance.In the second phase, a synthetic dataset was generated to represent the relevant climatic variables, given the scarcity of real-world measurements and the challenges associated with obtaining them locally. This dataset consisted of 3,000 samples for each system. The variables were selected based on previous studies[31-33].An Artificial Neural Network (ANN) was then developed and trained in Python to predict system performance. Solar Panels prediction model incorporated irradiance, temperature, humidity, wind speed, and dust concentration as inputs, whereas the wind-turbines model used wind speed, air density, wind direction, humidity, temperature, and atmospheric pressure. For both systems, the predicted outputs were voltage, current, and power. overall workflow of the proposed methodology is illustrated in Figure 1.

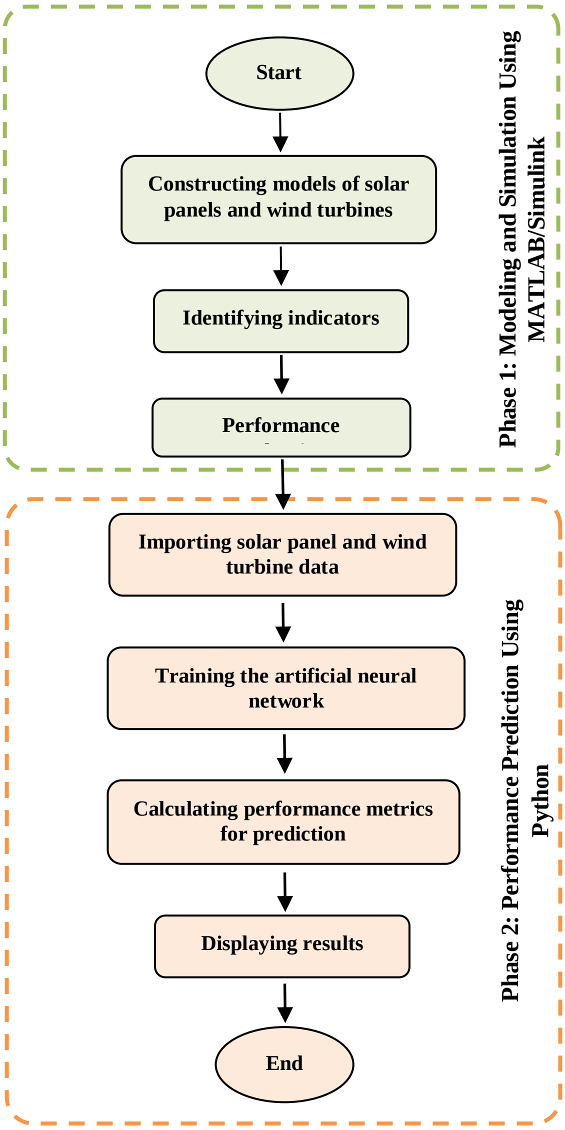

Figure 1: Research methodology flowchart

Regression Metrics

The regression model is evaluated during both the training and testing phases by comparing the actual values with the predicted ones. This assessment relies on a set of commonly used statistical metrics for model evaluation. The metrics employed in this study are presented below[34]:

1. Mean Absolute Error (MAE):

MAE is one of the fundamental statistical metrics, as it calculates the average of the absolute differences between the predicted and actual values. This metric reflects the overall magnitude of the error without considering its sign, whether positive or negative. It is mathematically expressed as shown in Eqn (8):

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|y_{i,ture} - y_{i,pred}\right| \quad (8)$$

Where: N is the number of samples, $y_{i,ture}$ is the actual value, and $y_{i,pred}$ is the predicted value.

2. Mean Squared Error (MSE):

MSE is a statistical metric used to assess the accuracy of a model by computing the average of the squared differences between the predicted and actual values. This metric gives greater weight to large errors due to the squaring operation. It is mathematically expressed as shown in Eqn (9):

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_{i,ture} - y_{i,pred})^2 \quad (9)$$

Where: N is the number of samples, $y_{i,ture}$ is the actual value, and $y_{i,pred}$ is the predicted value.

3. Root Mean Squared Error (RMSE):

RMSE is a derived form of the MSE obtained by taking the square root of the mean squared error. This approach restores the error metric to the same scale as the original data, making it more interpretable and easier to compare with real values. Mathematically, it is calculated as shown in Eqn (10):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_{i,ture} - y_{i,pred})^2} \quad (10)$$

Where: N is the number of samples, $y_{i,ture}$ is the actual value, and $y_{i,pred}$ is the predicted value.

4. Coefficient of Determination (R²):

Coefficient of determination (R^2) measures the strength of the linear relationship between the actual values and those predicted by the model. A value of 1 indicates optimal model performance, signifying a perfect match between actual and predicted values. R^2 is computed as shown in Eqn (11) [35]:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_{i,ture} - y_{i,pred}\right)^2}{\sum_{i=1}^{N}\left(y_{i,ture} - y_{true,mean}\right)^2} \quad (11)$$

Where: N is the number of samples, $y_{i,ture}$ is the actual value, $y_{i,pred}$ is the predicted value, and $y_{true,mean}$ is the arithmetic mean of the actual values.

5. Correlation Coefficient (R):

Correlation coefficient (R) quantifies the linear relationship between two variables and is also known as Pearson's correlation coefficient, distinguishing it from other correlation measures such as rank correlation. It is calculated as shown in Eqn (12) [36]:

$$R = \frac{\sum_{i=1}^{N}(y_{i,ture} - y_{true,mean})(y_{i,pred} - y_{pred,mean})}{\sum_{i=1}^{N}\sqrt{(y_{i,ture} - y_{pred,mean})^2}\sqrt{(y_{i,pred} - y_{pred,mean})^2}} \quad (12)$$

Where: N is the number of samples, $y_{i,ture}$ is the actual value, $y_{i,pred}$ is the predicted value, $y_{true,mean}$ is the mean of the actual values, and $y_{pred,mean}$ is the mean of the predicted values.

Classification Metrics

The performance of the classification algorithm is evaluated using the confusion matrix, which reflects the relationship between correctly classified samples and those incorrectly classified. A more detailed explanation of the confusion matrix is provided in reference [37]. This approach is used to assess the model's accuracy in predicting system performance. In this study, four metrics derived from true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) were employed. The evaluation metrics used to measure the model's accuracy are presented below [38]:

Accuracy

Accuracy is considered one of the simplest and most intuitive evaluation metrics, as it represents the ratio of correct predictions to the total number of samples in the dataset. It is commonly used to assess the performance of supervised learning algorithms by measuring how well the predicted results match the actual values. It is calculated as shown [38]:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})} \quad (13)$$

Precision

Precision represents the proportion of correctly predicted positive cases out of all cases that the model classified as positive. It is calculated using [38]:

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \quad (14)$$

Recall

Recall also referred to as sensitivity or the true positive rate measures the proportion of actual positive cases that were correctly identified by the model. It is computed using [38]:

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \quad (15)$$

F1-Score

The F1-Score is the harmonic mean of precision and recall, providing a balanced metric that reflects both the model's ability to avoid false positives and its effectiveness in detecting true positives. It is calculated using:

$$\text{F1} - \text{Score} = \frac{2 \,.\, \text{Precision} \,.\, \text{Recall}}{\text{Precision} + \text{Recall}} \quad (16)$$

Practical Implementation

The practical part of this study is divided into two main phases.The first phase involves the modeling and simulationof both solar panels and wind turbines using MATLAB/Simulink to evaluate their performance under different operating conditions.The second phase focuses on data analysis and prediction using the Python programming language, where various machine learning techniques were applied to enhance the accuracy of performance forecasting**.**

First: Modeling and Simulation

Modeling of Solar Panels

The solar panels were modelled by representing the equivalent circuit of the solar cell in MATLAB/Simulink, followed by an evaluation of the performance of three of the most common and widely used types of solar panels in Libya. These include the monocrystalline (M-Si) panel UDTS-50, the polycrystalline (P-Si) panel Aleo Solar 150S, and the amorphous (a-Si) panel Schott ASI-100.The modelling process was based on the catalogue values of each panel to ensure simulation accuracy. The parameters were extracted from the datasheets of each panel under standard test conditions (irradiance of 1000 W/m², temperature of 25°C, and air mass coefficient AM 1), as shown in Tables (2). The evaluation was carried out by studying the most influential variables on performance, namely solar irradiance and temperature [3].

For the monocrystalline and polycrystalline panels, the series and shunt resistances were obtained directly from their respective datasheets. In contrast, the amorphous panel did not provide these resistance values, necessitating the use of a simplified estimation approach based on the code presented in Appendix. This code employs an iterative algorithm derived from the panel's electrical data. The algorithm indicated that the series resistance is approximately 0.973 Ω, while the shunt resistance is around 127 Ω.

Table 2: Solar Panels Specifications [39, 40]

Parameter	M-Si	P-Si	a-Si
Open-Circuit Voltage (V_{oc}) (V)	21.6	43.40	40.9
Short-Circuit Current (I_{sc}) (A)	3.18	4.700	3.85
Number of Series Cells (N_s) (Ω)	36	72	72
Series Resistance (R_S) (Ω)	0.250	0.389	−
Shunt Resistance (R_{sh}) (Ω)	198.1	400	−
Temperature Coefficient (k_i)	0.0019	0.0024	0.0031
Maximum power voltage (V_{mpp}) (V)	17.5	35.40	30.7
Maximum power current (I_{mpp})	2.9	4.300	3.25
Maximum panel power (P_{mpp}) (W)	49.4	150.6	100
Fill Factor (FF) (%)	72	74	64
Efficiency (η)	12.83	11.76	6.9

Figure (2) present solar cell model developed in MATLAB/Simulink based on Eqn (1). The specific technical parameters of each solar panel were integrated into the model in order to simulate the behavior of the studied systems. The solar irradiance values were obtained from the Global Solar Atlas platform, which indicates that the average annual solar irradiance in Libya is approximately 2500 W/m²[8]. while the reference temperature was set at 25°C. These values were adopted as the baseline for evaluating panel performance under local operating conditions.

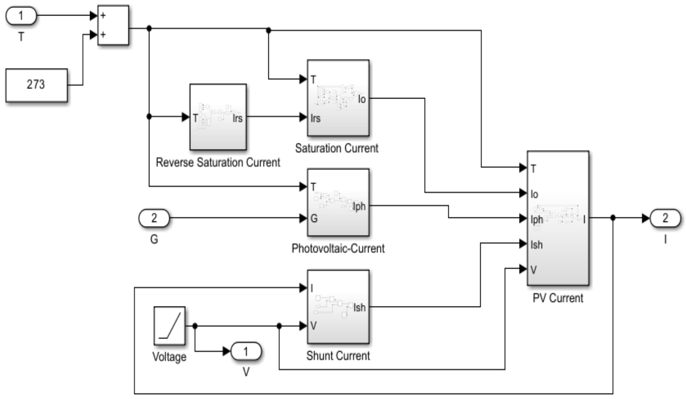

Figure 3: Solar cell model implemented in Simulink

Solar irradiance and temperature were defined as the primary input parameters in the model, as illustrated in Figure (2). The simulation process begins with calculating the reverse saturation current and the diode saturation current as functions of temperature. This is followed by computing the photocurrent generated from the incident solar irradiance. The leakage current resulting from the shunt resistance is then incorporated, after which the total output current and voltage are obtained. The performance of the solar panels under varying climatic conditions is evaluated using two fundamental indicators: efficiency and fill factor.

2.Modeling of wind turbines

A simulation model of horizontal-axis wind turbines was developed in Simulink. Two turbine types from different manufacturers were selected based on findings from previous studies, which indicated that these models are among the most common and widely used in Libya, in addition to their demonstrated economic and environmental benefits compared to other types. The selected turbines are the Acciona turbine with a rated power of 1.8 MW and the Gamesa turbine with a rated power of 2 MW. Vertical-axis turbines were not simulated due to their lower prevalence and limited deployment.

Table 3: Wind Turbines Specifications [41,42]

Parameter	Gamesa	Acciona
Blade pitch angle (β)	0	0
Rated power (MW)	2	1.8
Rated wind speed (m/s)	12	12
Rated rotational speed (relative to generator rated speed)	1	1
Maximum power at rated wind speed	1	1
Pitch-control gain [Kp, Ki]	[5,25]	**[5,25]**
Maximum blade pitch angle	45°	**45°**
Maximum pitch rate (deg/s)	2	2

During the research, we encountered a challenge due to the unavailability of data for these turbines from manufacturers or official sources. Following the approach adopted in previous studies that modelled wind turbines, we relied on the data reported in those studies, with a slight adjustment in the rated power to emulate the behaviour of the turbines investigated in this work. Table (3) presents the Specifications used in the simulation process.

Figure (4) presents a simulation model of a grid-connected wind turbine using an induction generator. The system begins with a 25 kV voltage source, followed by a three-phase transformer that steps the voltage down to 575 V to supply the generator. To enhance system stability, a 66 Ω resistor is connected between the neutral point n2 and ground. The model includes two inputs: wind for the incoming wind speed and trip for protection, with the frequency set to 60 Hz to represent common grid standards. The system also incorporates a three-phase capacitor bank to improve the power factor and compensate for reactive power. Active and reactive power are measured and converted from per-unit values into actual quantities. In this study, the efficiency of wind turbines is defined as a performance indicator representing the ratio of the electrical power output to the available wind power, as obtained directly from the Simulink wind turbine model. The efficiency term is used as a comparative performance metric rather than a strict aerodynamic efficiency, and it is consistently applied across all simulated wind turbine cases[16, 31].

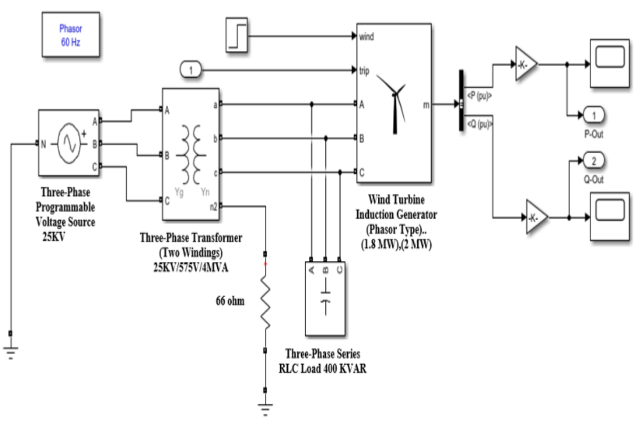

Figure 4: Wind Turbines Model in Simulink

Wind turbine settings configuration

Figure (5) illustrates the parameter configuration of the Gamesa wind turbine within the Simulink wind turbine model.

The required data were entered into the turbine parameter block, where the rated power was set to 2 MW and the rated wind speed was defined as 12 m/s, while the remaining parameters were kept unchanged to ensure a realistic representation of the turbine's operational behavior. The same procedure was followed to configure the parameters of the second turbine.

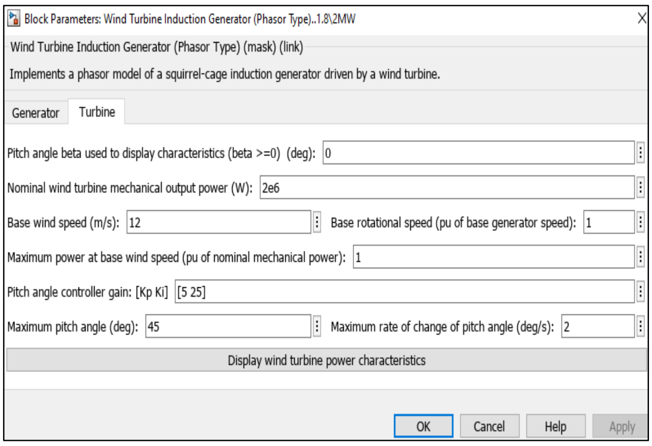

Figure 5: Configuration of the Gamesa turbine parameters

Second: Data analysis and performance prediction

In this stage, the Jupyter Notebook interface on the Anaconda platform was used as the primary environment for programming the model and carrying out prediction processes. Python was employed to develop the code required for building the Artificial Neural Network (ANN) model. Table (4) presents the Parameter of the neural network adopted for both the photovoltaic system and the wind turbine system.

The programming codes used in this paper are available in detail on my GitHub account and can be accessed through the following link: https://github.com/shalfathi-beep/Code-Phyton-for-Ann

Table 4: Neural Network Parameter

Parameter	Solar panals ANN Model	Wind turbines ANN Model
Number of Samples	3000	3000
Number of Inputs	5	6
Number of Outputs	3	3
Number of Hidden Layers	2	2
Hidden Neurons	64	64
Epochs	100	100
Training	%70	%70
Validation	%15	%15
Testing	%15	%15

Results and Discussion

The results presented in this section cover the stages of performance evaluation for both the solar panel and wind turbine systems, in addition to the prediction stage. The first stage involved performance assessment using the Simulink environment, where both systems were modeled and simulated. The focus was placed on examining the effects of solar irradiance and temperature on the efficiency and fill factor of photovoltaic panels, as well as analyzing the influence of wind speed on the efficiency of wind turbines. In addition, the error percentage between reference values and simulation results was calculated to evaluate the accuracy of the developed models.The second stage was dedicated to data analysis and performance prediction using artificial neural networks, based on relevant climatic variables. The figures and tables included in this section present the key findings obtained from both the evaluation and prediction processes.

Results of the First Stage: Modeling and Simulation

1. Solar Panels

Effect of Irradiance and Temperature on Efficiency

The results show that the efficiency of solar panels increases with higher solar irradiance, as illustrated in Figure (6). All panel types exhibit a rise in efficiency as irradiance increases, with the monocrystalline panel demonstrating the highest rate of improvement. This reflects its superior performance compared to the other types, where the increase in efficiency corresponding to the change in irradiance reached 27% from the lowest to the highest level.

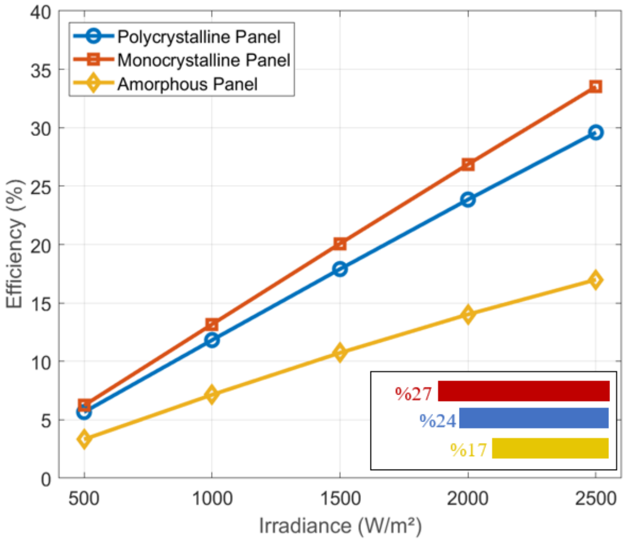

Figure 6: Effect of irradiance on the Efficiency of PV

Figure (7) illustrates the effect of temperature on the efficiency of solar panels. The results indicate a gradual decrease in efficiency as temperature rises. They also reveal differences in temperature sensitivity among the panels, with the amorphous panel being the least affected by the temperature increase. The reduction in efficiency corresponding to the change in temperature reached approximately 8% from the lowest to the highest temperature.

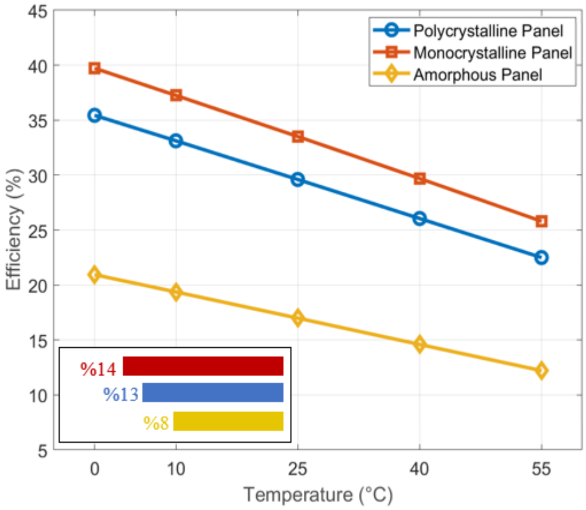

Figure 7: Effect of Temperature on the Efficiency of **PV**

Effect of Irradiance and Temperature on Fill Factor

results show that the fill factor remains nearly constant with varying levels of solar irradiance, as Figure (8) indicates no significant differences in its value as irradiance increases. This suggests that the effect of solar irradiance on the fill factor is limited and not substantial.

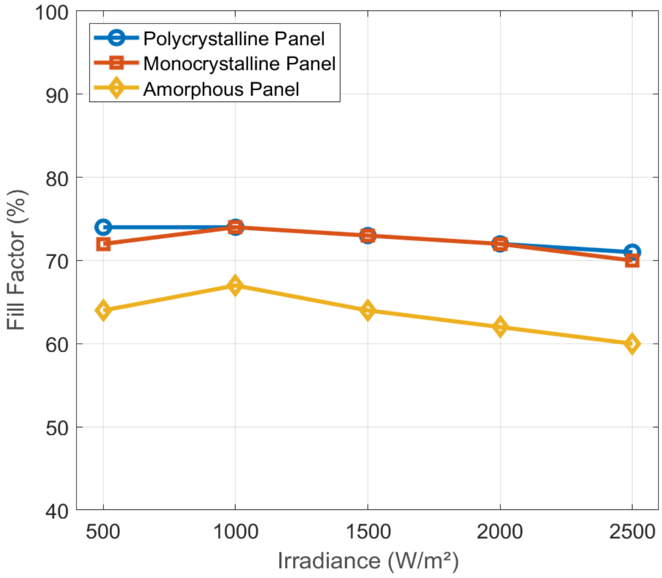

Figure 8: Effect of irradiance on the Fill Factor of PV

As for the effect of temperature, Figure (9) demonstrates that increasing temperature leads to a noticeable decrease in the fill factor for all the examined solar panels. This decrease is an indicator of the overall performance degradation of the solar panels as temperature rises.

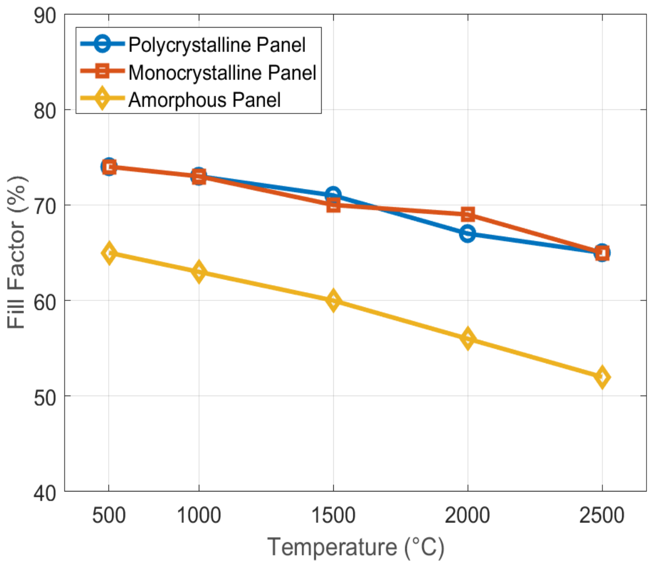

Figure 9: Effect of Temperature on the Fill Factor of **PV**

2. Wind turbines

Effect of wind speed on the efficiency of wind turbines

The results indicate a direct relationship between wind speed and turbine efficiency, where Figure (10) shows a significant increase in efficiency within the speed range of 8 to 12 m/s. The turbines begin to operate at high efficiency at 12 m/s, which is the rated design speed adopted to achieve optimal performance. Beyond this value specifically at 14 m/s the increase in efficiency becomes limited, suggesting that the turbine is approaching its maximum operational efficiency. The results show that both turbines achieve similar performance, with efficiency increasing by about 89% for the Acciona turbine and 90% for the Gamesa turbine from the lowest to the highest wind speed.

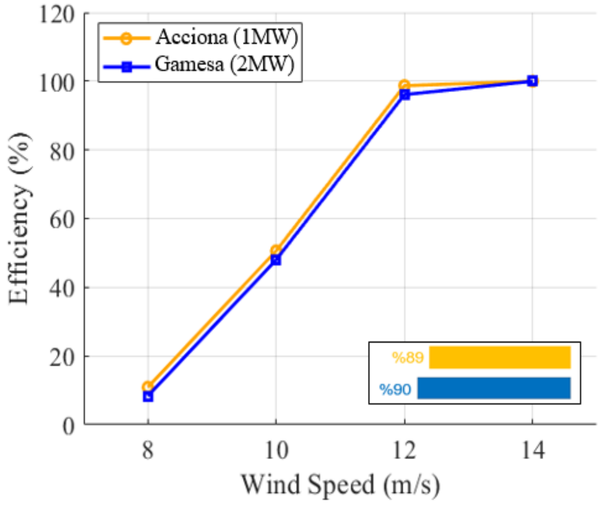

Figure 10: Effect of wind speed on the efficiency of wind turbines

3. Estimating the error percentage between the reference values and the simulation results

The error percentage estimation began by comparing the reference values with the simulation results for both the solar panels and wind turbines. For the solar panels, the reference values of efficiency and fill factor obtained from the datasheet were used, and the differences between these values and the model outputs were analyzed. In the case of the wind turbines, the efficiency was calculated from the simulation outputs and compared with the reference value of 100%. Based on Figure (11) for the solar panels and Figure (12) for the wind turbines, the results show that the error percentages were low, indicating the accuracy of the models used. Although minor differences exist, such discrepancies are expected since the simulation represents an approximate behavior of the system rather than an exact replication of real-world conditions.

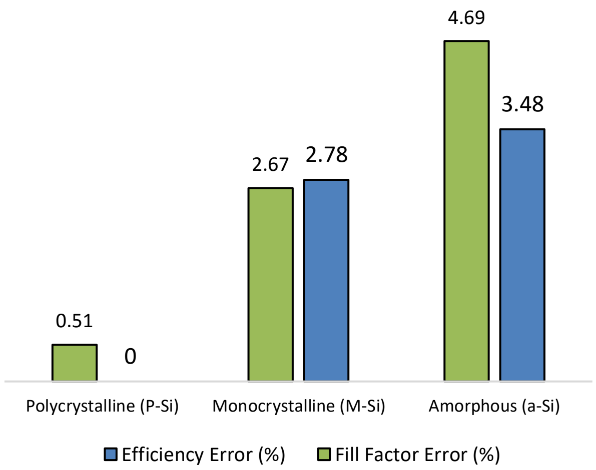

Figure 11 : Error Percentage of Solar Panels

Results of the Second Stage: Data analysis and performance prediction

1. Performance Prediction for Solar Panels

An Artificial Neural Network (ANN) model was employed to predict the performance of the solar panels. Table (5) presents the model evaluation results during the training and validation phases. The model was assessed using regression-based metrics to quantify the error percentage and estimate prediction accuracy. The low metric values indicate the model's high accuracy and strong capability in capturing the relationships between the inputs and outputs.

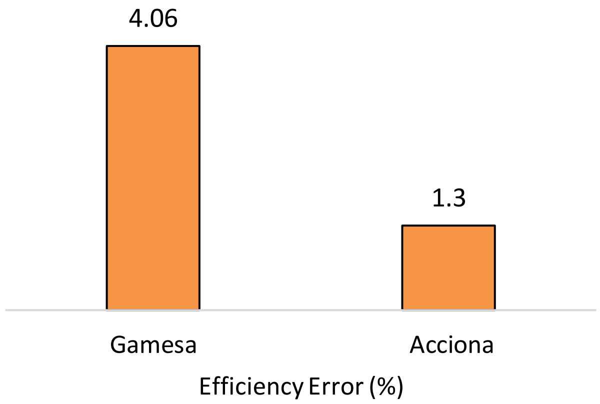

Figure 12 : Error Percentage of wind turbines

Table 5: Evaluation of the ANN Model for Solar Panels Using Regression Metrics

Total Dataset	MSE	MAE	RMSE
Training	0.0011	0.0255	0.033
Validation	0.0012	0.0268	0.035

The results presented in Table (5) indicate that the high values of both the correlation coefficient (R) and the coefficient of determination (R^2) reflect the reliability and accuracy of the model in prediction, as well as its ability to explain the relationship and variance between the actual and predicted values. This confirms the effectiveness of the model in predicting the key outputs of the solar panels—voltage, current, and power based on the climatic variables used as inputs [42].

Table 6: Correlation and Determination Coefficients for the Solar Panels

Model Outputs	R^2	R
Voltage (V)	0.960	0.980
Current (A)	0.972	0.986
Power (W)	0.980	0.990

The best model performance was achieved when predicting power, followed by current and then voltage, as shown in Table (6), based on the classification metrics. The superior prediction accuracy for power is attributed to the fact that power represents a direct outcome of the interaction between voltage and current with the climatic variables. This enabled the artificial neural network (ANN) to efficiently capture and represent the nonlinear relationships within the data [42].

2. Performance Prediction for Wind Turbines

The performance of the wind turbines was predicted using an Artificial Neural Network (ANN). Table (7) presents the training and validation results based on regression metrics used to evaluate the model. The results show that the model achieves a low error rate, indicating its high accuracy in capturing and representing the relationships between the input variables and the corresponding outputs.

Table (8) shows that the high values of both the correlation coefficient (R) and the coefficient of determination (R^2) reflect the model's accuracy in explaining the relationship and variance between the actual and predicted values of current and power in the wind turbines. In contrast, the voltage results demonstrate relatively lower accuracy, though they remain acceptable from a practical standpoint. The

Table 6: shows the performance evaluation of the ANN model for solar panels using classification metrics

Outputs	Accuracy	F1 Score	Recall	Precision
Voltage (V)	0.9377	0.9374	0.9340	0.9409
Current (A)	0.9470	0.9468	0.9433	0.9503
Power (W)	0.9627	0.9626	0.9613	0.9639

Table 7: Evaluation of the ANN Model for Wind Turbines Using Regression Metrics

Total Dataset	MSE	MAE	RMSE
Training	0.0031	0.0308	0.056
Validation	0.0039	0.0332	0.062

reduced accuracy in voltage prediction is attributed to its stronger dependence on internal factors within the electrical network rather than on climatic conditions. These factors include voltage regulation, reactive power control, and load variations. Consequently, the model faces greater difficulty in accurately representing voltage behaviour compared with current and power [43].

Table 8: Correlation and Determination Coefficients for the Wind Turbines

Model Outputs	R^2	R
Voltage (V)	0.650	0.806
Current (A)	0.998	0.999
Power (W)	0.998	0.999

Table (9) indicates that the model achieved its best performance when predicting current and power, followed by voltage, for the wind turbines, according to the classification metrics.

Table 9: Performance evaluation of the ANN model for Wind turbines using classification metrics

Model Outputs	Accuracy	F1 Score	Recall	Precision
Voltage (V)	0.7957	0.7802	0.7253	0.8441
Current (A)	0.9860	0.9859	0.9787	0.9932
Power (W)	0.9913	0.9913	0.9887	0.9940

Conclusions

Polycrystalline panel demonstrated the highest responsiveness to increased solar irradiance, with a 27% rise in efficiency between the lowest and highest irradiance levels. In contrast, the amorphous panel was the least affected by temperature, with an efficiency drop not exceeding 8%. The results also showed that the fill factor is more sensitive to temperature increase than to irradiance variationAdditionally, the study revealed a gradual increase in wind turbine efficiency as wind speed increased, reaching the optimal speed at 12 m/s, with an 89% increase for the Acciona turbine and 90% for the Gamesa turbine between the minimum and maximum speeds. This indicates a close similarity in performance between the two turbines. The simulation models produced very low error rates, reflecting high accuracy despite minor deviations inherent to approximate modeling.Furthermore, the artificial neural network model showed a clear reduction in error between actual and predicted values, demonstrating its ability to accurately represent system data and forecast performance. The model also achieved a high correlation coefficient when predicting power output, reaching 99.8% for solar panels and 98% for wind turbines, confirming its strong alignment with the real behavior of both systems. In addition, the model achieved high prediction accuracy 99% for wind turbines and 96% for solar panels highlighting its effectiveness in estimating power output based on the input data.

Recommendations for Future Work

study recommends the importance of considering climatic factors such as solar irradiance, temperature, and wind speed when designing and operating renewable energy systems to enhance efficiency. It also highlights the need to develop cooling solutions and thermal management strategies to mitigate the impact of high temperatures on solar panels. Furthermore, the polycrystalline module is recommended for regions with variable irradiance, whereas the amorphous module is more suitable for high-temperature environments.The study additionally advises the adoption of intelligent control systems to regulate blade pitch and rotational speed in wind turbines, noting that the Acciona and Gamesa turbines exhibit comparable performance and may be selected based on power requirements and site-specific operating conditions. The recommendations also include conducting regular maintenance, analyzing operational data, and integrating intelligent models with real-world datasets to improve prediction accuracy. Moreover, the study encourages expanding future research to investigate more complex operating conditions and to evaluate and predict the performance of hybrid solar wind energy systems.

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