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Machine learning based annual solar energy forecasting for enhanced grid integration of photovoltaic systems

Nandini K. Krishnamurthy[1], Anubhav Kumar Pandey[2,3,4], Sumana Sreenivasa Rao[2,3]
[1]Department of Electrical and Electronics Engineering, NMAM Institute of Technology, Nitte (Deemed to be University), Nitte, India
[2]Department of Electrical and Electronics Engineering, Dayananda Sagar College of Engineering, Bengaluru, India
[3]Centre for E-Mobility and Sustainability, Dayananda Sagar College of Engineering, Bengaluru, India
[4]Department of Electrical and Electronics Engineering, Visvesvaraya Technological University, Belagavi, India

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ABSTRACT

The increase in electricity demand is witnessed by many nations due to the rise in population and ongoing developments. To cope with energy requirements, countries are looking towards cleaner alternatives to reduce overreliance on energy generation from conventional resources. The introduction of artificial intelligence (AI) in real-world applications is acknowledged positively by experts as it enhances the performance and efficiency of the system. This paper reports the advancement of AI in harnessing renewable energy sources (RESs) to their true potential by leveraging their response when the grid is not able to fulfill the power requirement from conventional resources. Moreover, the prediction also remains a challenge with renewables due to their volatile behavior, especially with solar-based energy generation. This issue is also addressed by interfacing AI-enabled applications and the difference between true and predicted values for one year is observed. The result reveals that the true response aligns with the predicted response, which ensures the ability of AI to harness solar energy by consuming minimal time. The proposed approach is also promising from the utility operators' and end users' perspectives in designing any large-scale renewable projects for sustainable development and also encourages the utilization of renewables to a larger extent.

Corresponding Author:

Anubhav Kumar Pandey
Department of Electrical and Electronics Engineering, Dayananda Sagar College of Engineering
Bengaluru, Karnataka, 560078, India
Email: anubhav-eee@dayanandasagar.edu

1. INTRODUCTION

There is a growing need for electricity and as renewables are promoted in every nation, traditional sources like fossil-based generation are retiring in phases. Renewable energy sources (RESs) are already gaining popularity due to their abundance, as they are not going to deplete anytime soon. This transition from conventional to RESs is now under consideration to enable a renewable and sustainable planet, but the primary challenge is their integration with the utility grid. The incorporation of renewables will change the energy landscape, which seemed unrealistic almost a decade back and will eventually become the need of the hour.

The integration of renewables in the energy mix is not a pressing issue, but it becomes a prominent one when the share of RESs increases. This action requires proper management as the inertia of the traditional set-up disturbs and to handle this challenge, utility operators are hesitant when it comes to the scheduling and dispatch of electricity. In light of this brief note, harnessing artificial intelligence (AI) comes as a blessing in disguise, which not only makes the integration of renewables seamless but also makes it relatively easier for the utility operators from a management and control perspective.

The relevant literature is reviewed, which underlines the work reported in this domain and to begin with, Zaharuddin *et al*. [1] discussed the role of AI in the energy sector to facilitate the operation and management of RESs. AI is utilized to enhance the efficiency of renewables in line with optimizing resource management. It has been claimed that utilizing AI can not only escalate the energy management portfolio (EMP) but also enhance the overall structure of the energy systems. Kristian *et al*. [2] discuss the role of convolutional neural network (CNN) and long short-term memory (LSTM) in improving resource management efficiency by predicting the accurate data of RESs, followed by the optimization and finally the automation of weather-dependent renewables. Accurate predictions are not only helpful for the decision-makers but also provide information to the utility operators so that the balance between supply and demand can be maintained with minimal errors. Agomua *et al.* [3] presented a detailed study regarding the prediction of energy consumption through linear regression and employed PSO for resource allocation in energy-efficient cloud computing environments. The optimization technique is particularly used to minimize the unit count in cloud resource allocation. Although there were some fluctuations in the initial phase as the iteration progressed, subsequently, stabilization is observed as per the Author's claim. Finally, there has been an improvement of 83% in the accuracy in the context of forecasting future resource demand. Jha *et al*. [4] explained the role of AI in attaining the goals of renewable energy in the power sector. The study listed applications of viable AI technologies in various renewable sources (RSs), which can be a driving force in changing the landscape of the energy sector for a just energy transition. Interfacing AI with RSs can not only enhance the performance of sources but can also play a decisive role in framing new policies to reduce the threats related to cybersecurity. Rashid *et al*. [5] offered a review regarding the importance of AI in the renewable energy domain (RED) to help integrate large-scale renewables in modern power systems. Primarily, three main areas where AI can improve the existing performance are discussed viz., prediction and forecast of renewables following their integration in the energy mix and finally optimizing the energy system to leverage its true potential. The authors also discussed big data structuring which can analyse the event of failures, risk-based analysis, maintenance as and when needed and finally the consolidation of asset management. Boza and Evgeniou [6] offered an economic model to reduce the integration of renewable energy in the power sector through AI technology. The potential of value-based creation is explored and the role of AI in enhancing this aspect is suggested by discussing multiple cases. Generation and demand forecasting are suggested to mitigate the profile and balance cost-related issues, along with an appropriate market design that is more flexible from an operational point of view. The research concluded by highlighting that AI offers promising avenues when linked with renewable energy generation and can also be a potential tool in reducing the integration costs associated with it. Bennagi *et al*. [7] reviewed the impact of AI and the leverage it provides in the field of renewable-powered energy systems. Interfacing AI techniques can not only improve the overall efficacy of the system but also be a major stimulant in cost reduction and minimizing complexities as well. Various approaches to AI are listed that can accelerate innovations in the renewable energy field. The authors have also discussed the AI-related applications in control and management aspects and concluded their study that a correlation between machine learning and deep learning models will be a potential solution in making renewable energy systems (ESs) smarter. The researchers [1]–[7] explores the role of AI in renewable energy prediction.

Rusilowati *et al*. [8] emphasize the role of AI in optimizing the RESs by combining quantitative as well as qualitative methods. Apart from improving energy efficiency, AI also helps in reducing waste and supports sustainability. By implementing AI, there is a substantial increase in the cost-benefit of solar, wind and biomass energy. Ahmad *et al*. [9] emphasized the need for developments going on digital technologies front, which has the potential to change the energy landscape. The incorporation of AI techniques in the energy industry is expected to enhance the control and management aspects. Moreover, the potential of AI in expanding the future and digital energy market in line with the impact of big data is discussed. The support of AI in advancing the energy field is also highlighted, particularly the role of deep learning can simplify energy trading in real-time with minimal errors. AI techniques are powerful in making the power network more robust and resilient enough to initiate self-healing as and when required during peak operational hours. Pandey *et al*. [10] performed optimized scheduling of a virtual power plant (VPP), which can perform effective aggregation of associated renewable resources. The economic aspect of VPP is underlined in this work and the profit margin is improved by employing advanced optimization techniques. The study concludes by stressing the fact that reducing reliance on fossil-based resources is becoming the need of the day in the present time to promote the adoption of renewables on a large-scale integration. The researcher [8]–[10] describes the role of AI in optimizing various resources.

Danish *et al.* [11] discuss a multi-disciplinary approach by curating exhaustive literature that dates back from 1957 to 2022, as far as AI applications are concerned, especially the role of AI in energy trading platforms. The study further carried out by emphasized the significance and essentialities of AI and machine learning (ML) in power systems, which can not only advance the overall operation but can also facilitate large penetration of renewable energy to further advance the smart grid technologies.

The main challenge lies in making the centralized structure flexible through software-based technologies, as enormous data exchange is required through information and communication technologies (ICTs) and introducing AI in ICTs will only improve the existing data transfer capability. Cheng and Yu [12] go beyond AI and discuss the new generation of AI i.e., AI 2.0. The authors further emphasized the role of AI 2.0 in advancing the rapid development and improvement of smart power and energy in electric power systems. Overall, a detailed survey regarding AI, AI 2.0, ML and energy internet (EI) is carried out in power system fields. Finally, analysing, judging, optimizing, and decision-making make the AI the most viable tool to further exemplify the energy times classification, energy 1.0 to energy 5.0, which ranges from dormant energy-based natural resources to the advanced systems based on parallel energy transfers to make this sector more responsive. Kumar *et al*. [13] highlighted the concept of enabling AI and internet of things (IoT) based multi-channel communication in modernized power system structures to enhance the capability of distributed energy resources (DERs). The authors further emphasized that lucrative features through AI i.e., detect, react, and pro-act, can enhance the resiliency and stability of electrical networks. Dellosa and Palconit [14] discussed the impact of AI in managing power system operations along with maintaining the control aspects of renewable-powered energy systems. Various AI-based conventional and advanced techniques i.e., artificial neural network (ANN), backpropagation neural network (BPNN), Radial basis function neural network (RBFNN), seasonal autoregressive integrated moving average (SARIMA), and adaptive neuro-fuzzy inference system (ANFSIS), are discussed which are utilized to predict solar power. However, ANN is emphasized in this work due to its higher accuracy, relatively shorter average computation time and eventually a cost-effective tool. Ahmad *et al*. [9] emphasized the need for developments going on the digital technologies front, which has the potential to change the energy landscape. The incorporation of AI techniques in the energy industry is expected to enhance the control and management aspects. Moreover, the potential of AI in expanding the future and digital energy market in line with the impact of big data is discussed. The support of AI in advancing the energy field is also highlighted, particularly the role of deep learning can simplify energy trading in real-time with minimal errors. AI techniques are powerful in making the power network more robust and resilient enough to initiate self-healing as and when required during peak operational hours. The researchers [9], [11]–[14] explores the importance of AI in grid integration and power system network upgradation.

The relevance of renewables in promoting the sustainability aspect from a holistic point of view is discussed which can also uplift the overall enhancement in the energy sector by enabling AI-based techniques. Various AI-driven methods also play a huge role in a true prediction of generation from the variable renewable energy sources. This is followed by securing the threats introduced when AI-based techniques are employed and preventing these fragile cyberattacks which can lead to disturbance in the field of the energy sector. Following the analytical prediction of production and consumption, optimizing these patterns can not only save energy but can also facilitate surplus power to fulfil future requirements. Nonetheless, there exist some challenges in the adoption of AI in the energy domain and exhaustive policies will be a key in deploying these advancements to enable state-of-the-art robust methods by maximizing precision and accuracy. Annual solar forecasting is typically utilized for capacity planning, financial modelling, infrastructure development, policy and procurement. Long-term forecasting helps utilities and grid operators to determine how much solar capacity is required to meet future demand. Investors and developers rely on long-term forecasts to assess the financial viability of solar projects. To sum up, this work emphasizes AI-driven approaches for future trends that can not only leverage the potential of existing renewable-based energy systems but also transform the energy sector, technologically advanced by improving their performance.

The rest of the paper is organized as follows: section 2 discusses the materials and methods, in which the status of sustainable energy sources, along with the artificial intelligence implications. Section 3 comprises results and analysis, followed by section 4, in which discussions are listed and finally section 5 consists of conclusion, limitations, and future work.

2. METHOD

2.1. Sustainable energy sources

The energy sector plays a key role in deciding the future of any nation and they are of utmost importance to achieve sustainability in the energy landscape. The majority of the energy resources are often based on conventional approaches, which are fossil and gas-based power plants for electricity generation, which are not sustainable. In the past decade, there has been a paradigm shift in the selection of these resources to improve the way electricity is produced, following which renewables are now considered the major catalysts towards transitioning into a clean and green ecosystem. The primary renewable resources are solar and wind-based generation, which currently hold the maximum amount of share in the energy mix and are therefore considered as most prominent contributors. Earlier, the primary reason for the limited share of renewables in the energy mix was the lack of technological advancements, but as AI-based techniques are evolving, this issue will be mitigated shortly. Also, intermittency is another aspect that makes solar and wind sources unpredictable and relatively less reliable. However, this can be compensated by installing energy-based storage systems to accumulate the surplus power generated when the sun is shining the most and the wind is blowing impeccably to ensure an uninterrupted power supply.

The global inequalities concerning energy demand also need to be analyzed, as the developed and renowned nations may have enough financial capital to invest in renewables, which developing nations may not have and therefore immediate shift to renewables is not possible. However, the rapid increase in energy demand can be fulfilled by installing solar rooftop solutions in residential premises and utilizing the true potential of solar power and this is very much possible as Bharat is considered as Surya Putra country, specifically with context to the Indian perspective. This way, renewable-powered energy solutions can slowly increase their overall share in the energy mix and eventually overtake the conventional-based generations by merging the advancements in renewable technologies with AI-powered energy solutions. The Government of India (GoI) is driving the change by putting maximum efforts through their excellent policies and schemes viz., PM Surya Ghar: Muft Bijli Yojna, and PM Kusum Yojna [9], [15]. These innovative schemes will not only accelerate the renewable-specific target for India but also empower its citizens to become Atmanirbhar (self-reliant India) on the energy front. It is important to note that the nation's schemes must be supported by international communities to advance sustainable actions that not only improve the ecosystem of the nation but also highlight the nationally development contributions (NDCs) to empower a sustainable energy future. Nonetheless, economic feasibility is important as shifting completely to renewables without any robust backup will make the power system vulnerable by affecting its operations. Hence, swift transitions are not only viable but also practical from both government and utility points of view in achieving the energy, environmental and economic goals. This sustainable energy transition (SET) is therefore becoming the need of the present day and AI is anticipated to play a major role in this transition. The world electricity production from renewables in percentage by 2023 is given in Figure 1 [16].

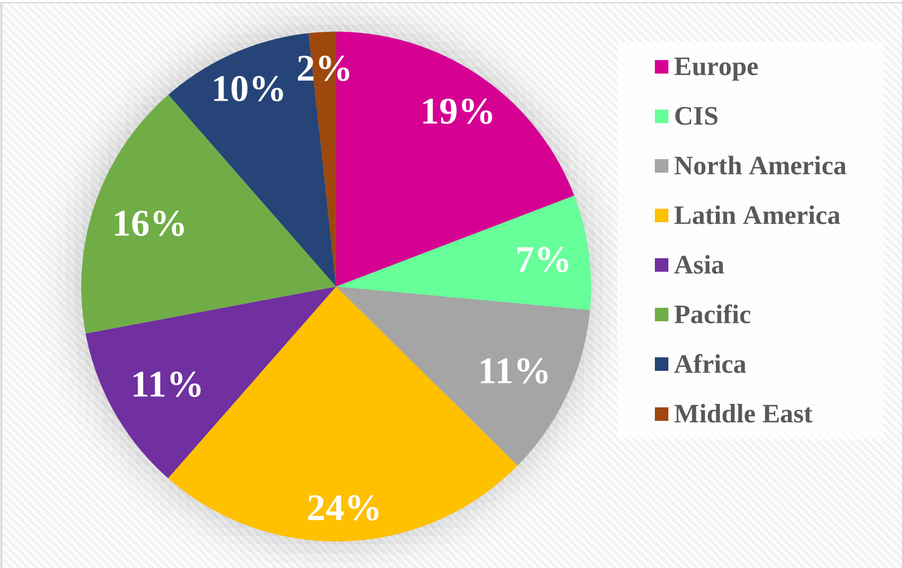

Figure 1. Percentage of electricity production by renewables in the year 2023

The maximum contribution is from Latin America, followed by Europe, and 11% of electricity is produced from renewables in Asia by 2023. The variety of RESs and their possible combinations in hybrid configuration setup are listed in Table 1 [4].

Table 1. Categories of sustainable energy sources and their combinations

Energy resource	Single type	Hybrid configuration
Wind energy	a. Wind turbine	PV-wind ESs
	b. Wind mill	PV-wind-batteries ESs
Solar energy	a. Photovoltaic	PV-wind-batteries ESs
	b. Thermal	PV-wind-hydrogen ESs
Geothermal energy	a. Dry steam power plant	PV-wind-batteries-hydrogen ESs
	b. Flash steam power plant	PV-hydrogen ESs
	c. Binary steam power plant	
Hydro energy	a. Large hydro	PV-hydrogen ESs
	b. Small hydro	PV- batteries-hydrogen ESs
	c. Micro hydro	Wind-hydrogen ESs
Ocean energy	a. Wave energy	Wind-hydrogen ESs
	b. Tidal energy	Wind-diesel-hydrogen ESs
	c. Ocean thermal energy	Wind-diesel-batteries ESs
Bioenergy	a. Biogas	PV-diesel-batteries ESs
	b. Liquid biofuels	
	c. Wood	

2.2. Data source for solar energy

The various solar energy data provider and their details are provided in Table 2 [17]. In the present paper measured PV data available on GitHub is used for the analysis.

Table 2. Data source provider of solar energy

Data source provider	Type (model/measured)	Description
NREL (NSRDB)	Model	Satellite-based irradiance data is used
PVsyst (Meteonorm)	Model	Synthetic data based on historical weather patterns
Solargis	Model	High-resolution solar resource data
Renewables.ninja	Model	Global PV simulation tool using real analysis data
PVGIS (EU)	Model	Historical and meteorological yearly data are provided by the European Commission
Measured vs simulated PV (Github)	Measured	Real PV output data from installations
OSM-MEPS (IEEE Data Port)	Measured	High-resolution irradiance data across multiple regions

2.3. Artificial intelligence for sustainable energy solutions

Sustainable energy technologies, including biomass, wind, hydropower, solar and geothermal, were firmly established and continuously emerging before the implementation of AI. Improvements in efficiency, cost reduction, and environmental considerations were the main goals of these technologies' development, even though AI has certain restrictions and difficulties in implementation. One of the main lacking aspects was the reliance on conventional methods for data analysis and decision-making, which often lacked real-time insights and predictive competencies. The added expenses of infrastructure, data collection, and algorithm training that came with incorporating AI into RESs, particularly in less developed regions, hindered the adoption. Concerns were also raised about data security, privacy, and the possibility that AI algorithms will worsen prejudices or disparities in energy distribution and access [18]. With the incorporation of smarter systems like AI-based techniques, RESs are growing more sophisticated, resilient, and responsive. AI plays a major role in SE, such as the prediction of energy consumption of the solar system, the prediction of wind speed, and solar radiation. Though understanding the intricate thinking of a human brain is a difficult task to solve, AI aims to comprehend human thinking to create intelligent entities that will perform efficiently for some challenging problems. The difficulty of manual computing was lessened by advancements in the field of AI. The application of AI in various sustainable resources is shown in Figure 2 [4].

The solar energy prediction using machine learning algorithms is presented in Figure 3. According to the literature, AI is mainly adopted to predict sustainable power, cyber-attacks in the renewable energy field and optimize the intake of sustainable energy with growing technology, as shown in Figure 4 [19]. AI can predict energy production from renewable sources like solar and wind by analyzing weather patterns and historical data. This helps in better planning and utilization of energy resources in a sustainable manner.

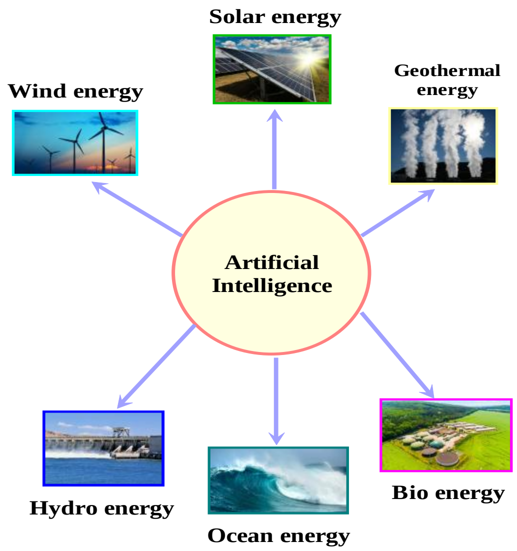

Figure 2. AI application in various sustainable sources

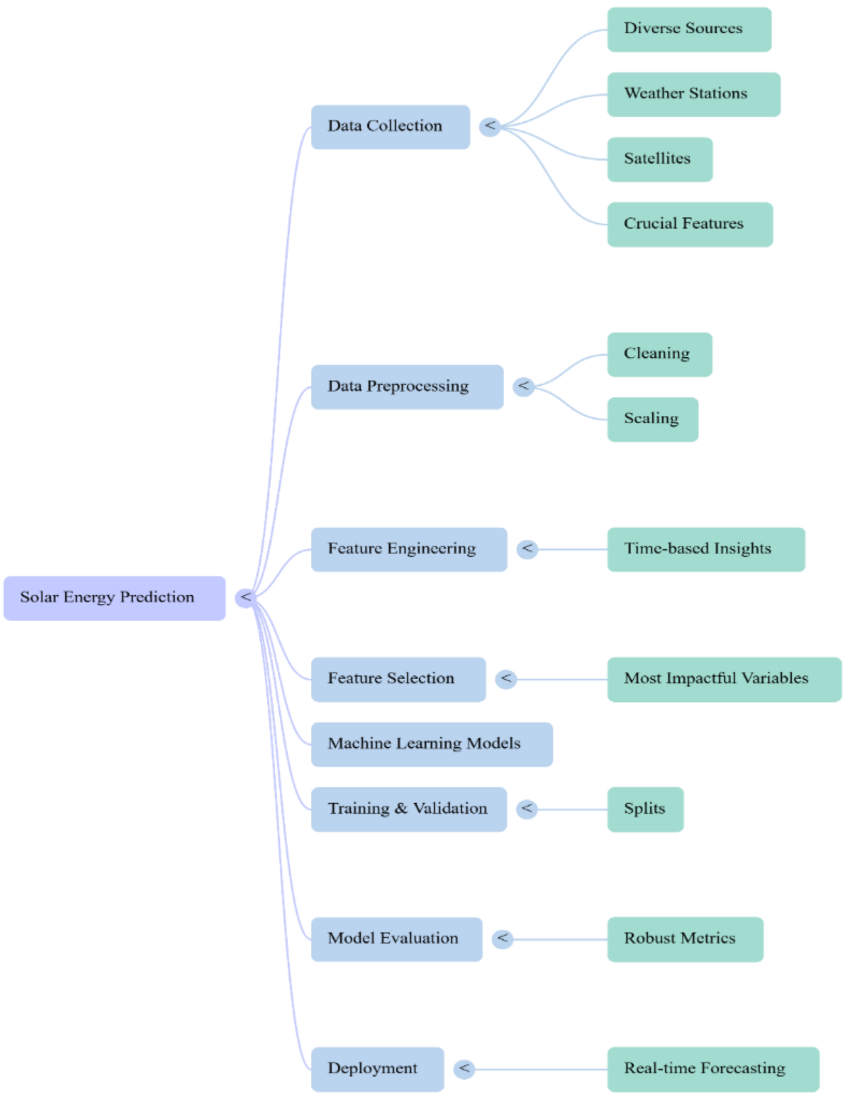

Figure 3. Solar energy prediction using machine learning algorithms

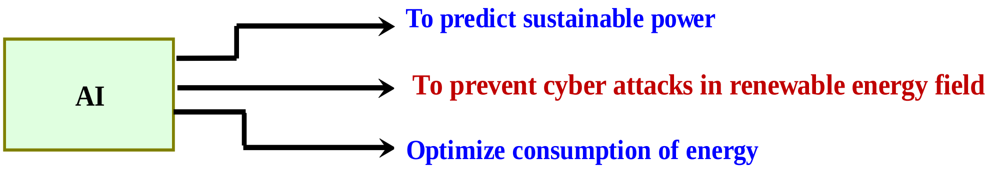

Figure 4. Application of AI in the field of sustainable energy

A workflow describing the AI pipeline is given as follows:
Step 1: Data acquisition - load data from the source
Step 2: Data preprocessing - clean the data
Step 3: Feature engineering - extract relevant features
Step 4: Model selection - choose an appropriate model
Step 5: Train/test split - split data into training and testing sets
Step 6: Model training - model on training data
Step 7: Model evaluation - predict on test data
Step 8: Inference - predict on new data
Step 9: Deployment

Developed a model using an echo state network convolutional neural network (ESNCNN) platform to find an energy equilibrium between the grid and energy production resources [20]. Different machine learning approaches, specifically deep learning methods, utilized for the prediction are compared effectively [21]. Different machine learning approaches used for load, frequency, and voltage prediction in power systems are compared comprehensively and proposed a machine learning predictive approach using network topology [22]. The RESs selection and sizing optimization is performed under multi multi-objective approach. The performances in minimizing the multi-objective functions for the on-grid and off-grid microgrids are verified [23]. The virtual power plant comprising renewable energy sources cost of operation is optimized by Gold Jackel optimization [24]. The non-linear optimization methods are applied to optimize hybrid microgrids, which include solar, wind and diesel energy sources. The total system cost is minimized while maintaining the reliability [25].

The digital green supply chain implementation potentially improves corporate eco-innovation. The organizational structure, key drivers' technology, human factors and environmental context strongly influence both internal integration and external collaboration [26]. The digital adoption and innovation performance in small and medium-sized enterprises plays a crucial moderating role is explored. The digital transformation is an integrated system where interconnected components collectively enhance innovation [27]. AI digital employee adoption drives future sustainable innovation in TikTok-based online retail, using the adoption innovations future performance framework grounded in the antecedents' behaviour consequences model [28].

Solar energy is uncertain in nature, influenced by weather, cloud and time of day. Accurate forecasting is crucial for grid stability, efficient distribution and energy storage. The AI is revolutionized in the area as follows: use of advanced machine learning models, satellite and sensor integration, hybrid and ensemble systems and analysing the real-world impact. There are several challenges and opportunities for more research when it comes to using AI in renewable energy research. The intricacy and cost of AI algorithms used in the planning, development, and management of RESs must be the primary focus. For these models to be widely used and scaled, they must be made more affordable and simpler. The AI approaches in various sustainable sources are listed in Table 3 [4].

Table 3. AI approaches in major sustainable energy sources

Energy sources	Single type	Hybrid type
Wind energy	BPNN, ANFIS, ADLINE, and fuzzy methods	Wind speed and wind power prediction
Solar energy	BPNN, adaptive neuro-fuzzy inference system (ANFIS), and regression methods	Solar radiation, energy, and power prediction
Geothermal energy	BPNN, ANFIS, EA, and fuzzy logic	Geothermal power prediction, map generation, and site location modelling
Hydro energy	BPNN, KNN, ANFIS, and fuzzy logic	Hydropower plant scheduling, river flow prediction, and power discharge estimation
Ocean energy	BPNN, ANFIS, and fuzzy logic	Sea level prediction and wave parameters prediction
Bioenergy	BPNN, GRNN, and RBFNN	Density prediction and prediction of biogas

3. RESULTS

Numerous learning theories, such as neural, statistical, and evolutionary learning, were created in literature publications, which are used in the development of AI. Several researchers discussed neural networks (NN), which are the most frequently utilized learning algorithms. The major classifications of AI approaches are ML techniques, and metaheuristic algorithms (MA). ML techniques are further classified as deep learning (DL), ANN, principal component analysis, bayesian model averaging, support vector machine and random forest. In the present work, an ML-based supervised learning technique (SLT), linear regression (LR) method, is applied for annual solar energy forecasting (SEF). This forecasting extends for the subsequent 365 days and provides insights for the upcoming days. SEF optimizes energy management systems and helps in optimizing resource allocation based on precision and accuracy. The LR model uses a set of independent variables such as meteorological, temporal and system configuration that influence the solar output. The LR models the relationship between input features and the target output. The flow of the model is depicted in Figure 5. The predicted solar energy is evaluated on the basis of mean squared error (MSE) and R-squared values. The non-linear effects can be captured by extending the model to polynomial regression. The LR model provides a transparent and interpretable baseline for solar energy prediction. While it may not capture complex non-linear dynamics, its simplicity and speed make it ideal for initial modeling, benchmarking, and integration into larger forecasting scenarios.

Figure 5. Linear regression model flow

The model captures the most relevant predictors of output by avoiding overfitting. The model is selected based on the physical relevance, statistical significance and model interpretability. Time-based split is employed for the analysis. Solar energy technology is advancing in multiple horizons and the interfacing of ML will only improve its effectiveness. These processes excel in modeling intricate relationships among complicated patterns of weather data, PV components, location and improving the overall forecasting precision. A one-year prediction horizon is applied for annual solar energy output. The simulation is performed on an Intel (R) Core (TM) i5-11300H @ 3.11 GHz, 8.00 GB RAM. The true values of solar energy for 365 days are shown in Figure 6. The electricity generated largely depends on the solar irradiation and location. The numerical results are listed in Table 4. The gaussian process regression tended to have an RMSE of 1.4006 e+11and an R-squared nearer to 1 and shows how the regression fits the line data. The maximum energy of 3.62×10^{7} W/m^{2} and the minimum energy of 2.18×10^{7} W/m^{2} are generated. The predicted values of solar energy over a year are shown in Figure 7. True responses are very near to the predicted values and the true response versus predicted response is shown in Figure 8.

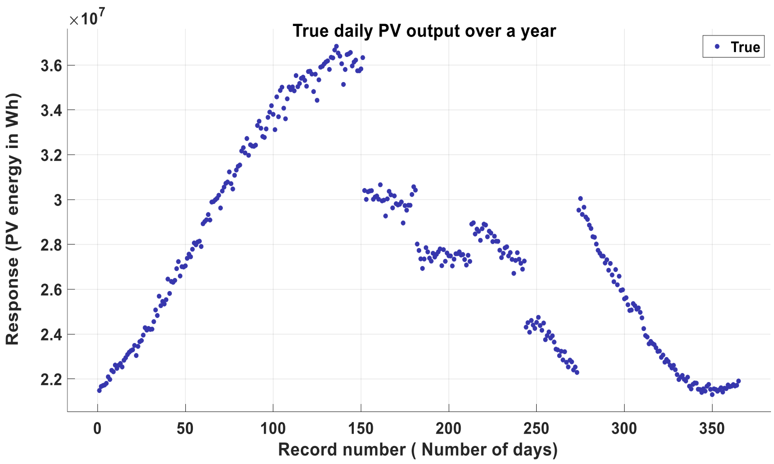

Figure 6. True values of solar energy over a year

Table 4. Various AI approaches applied in major sustainable energy sources

Parameter	Rational quadratic	Linear SVM	Robust linear regression
RMSE	3.7425 e+05	4.2576 e+06	4.1065 e+06
R-squared	0.98	0.07	0.14
MSE	1.4006 e+11	1.8127 e+13	1.6863 e+13
MAE	2.7273e+05	3.1579e+06	3.1932e+06
Training time	12.828 sec	3.362 sec	2.901 sec

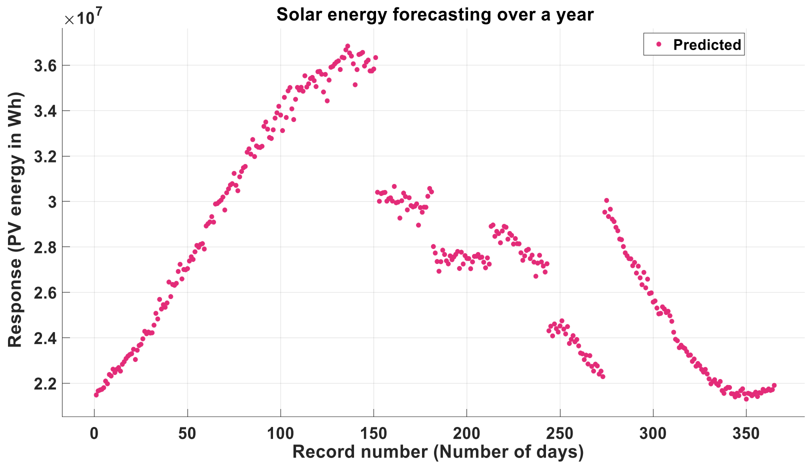

Figure 7. Predicted values of solar energy over a year

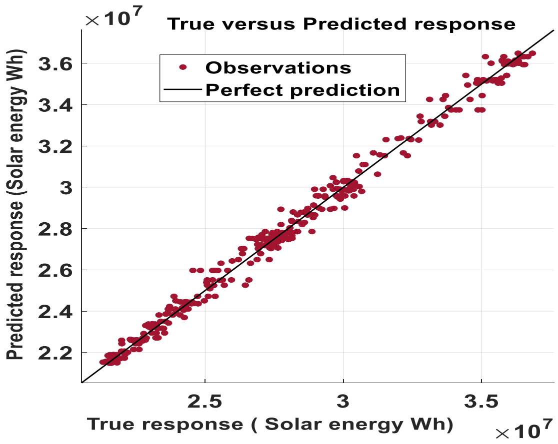

Figure 8. True versus predicted values of solar energy

4. DISCUSSION

The incorporation of renewables often faces uncertainty due to their unpredictable nature and that is why they are called variable renewable energy sources. The volatile nature of renewables often poses challenges in predicting the power generation as the intensity varies based on the day and night. These uncertainties can be addressed by incorporating AI-based method, which makes the forecasting and prediction accurate without any manual intervention which making these techniques a potential solution. This work emphasizes the importance of applying AI technology to enable the renewable integration with the grid by reducing the uncertainties associated with it.

Photovoltaic (PV) energy is poised to become a major global electricity source due to its abundance, affordability and scalability, and PV forecasting is a key element in its successful integration and utilization. It enables better grid management, facilitates the efficient use of energy storage, enhances grid stability and supports economic decision-making for both individual solar users and larger utility-scale projects. However, the variable nature of weather poses challenges, making accurate PV energy forecasting, which reduces generation-load mismatch and supports PV integration. Automating circuit breakers and relays under fault conditions, identifying and preventing lightning strikes on transmission lines, enhancing geothermal plant efficiency through IoT and AI, and controlling load demand for wind and solar power farms during severe weather are some of the major real-time challenges. Although additional and in-depth research may be required to confirm other associated challenges of AI techniques, like security threats, data scarcity or cost estimations.

There is a lot of scope for further research related to the accessibility of data, safeguarding models, security threats, optimization of AI integration, microgrids and SES's operational independence with AI [18]. Annual forecasting has a time horizon of one year, whereas short-term forecasting has minutes to days. Annual forecasting helps in long-term planning, investment and it requires historical data for analysis. Short-term forecasting helps in grid operations, energy trading and load balancing. Real-time weather data is required for the analysis. Strategic implications for grid operators planning renewable integration are enhanced grid stability, optimized resource allocation, support energy trading, pricing, infrastructure planning and unit commitment decisions. Limitations under extreme weather conditions are reduced accuracy during anomalies, sensor and module vulnerability and model rigidity.

5. CONCLUSION

This paper emphasizes the need for RESs in the overall energy mix to fulfill the ever-increasing demand for electricity. Renewables are a viable option over conventional-based electricity generation, but their volatile nature remains a challenge for the utility operators, which hinders the progress towards a swift energy transition. To overcome this barrier, an AI approach is utilized to alleviate the true potential of RESs, which can increase the prediction accuracy. Various AI-related approaches for RESs are discussed along with their wide applications and their possible combinations to leverage the power production capacity in a hybrid manner. The true and predicted values are also determined through AI for 365 days and the result reveals the precision and accuracy due to the state-of-the-art AI-based technological advancement.

It is observed that utilizing AI for RESs not only enhances the responsiveness of solar-based energy generation and at the same time reduces the prediction error rate to a considerable extent. Therefore, this work has the potential to be a foundation for aspiring researchers and policymakers to intensify the utilization of AI as long as it satisfies the need for power without much complexity. This work does have a few limitations i.e., integration of AI required in the energy sector is suggested, but its adoption on a large scale is subject to further exploration regarding this technology. Also, the wide acceptance of AI is not encouraged by everyone when it comes to a compromise between the existing jobs of skilled laborers. Therefore, these points are to be taken into consideration while adopting AI at a large scale to avoid any detrimental consequences.

The present work does have a few limitations i.e., integration of AI required in the energy sector is suggested, but its adoption on a large scale is subject to further exploration regarding this technology. Also, the wide acceptance of AI is not encouraged by everyone when it comes to a compromise between the existing jobs of skilled laborers. Therefore, these points are to be taken into consideration while adopting AI at a large scale to avoid any detrimental consequences. The quality issues associated with the data reduce accuracy and result in unreliable predictions. Poor generalization, limits scalability, risk of overfitting, grid integration challenges and high computational cost.

Future work will consider the balancing of environmental, as well as social and economic aspects, while addressing sustainable energy solutions through AI applications. Design an AI control architecture for hybrid microgrids and develop a real-time forecasting framework using ensemble learning and uncertainty quantification. Introducing a digital twin of a hybrid MG with real-time forecasting applications to revolutionize the energy sector.

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Nandini K. Krishnamurthy	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	✓
Anubhav Kumar Pandey	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓	✓	✓
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C : **C**onceptualization
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So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [AKP], upon reasonable request. GitHub repositories: https://github.com/Nandini997/Code_ML_Forecast.

REFERENCES

[1] Zaharuddin, S. Audiah, Y. P. A. Sanjaya, O. P. Daeli, and M. Johnson, "Transforming Energy and Resource Management with AI: From Theory to Sustainable Practice," *International Transactions on Artificial Intelligence (ITALIC)*, vol. 2, no. 2, pp. 158–163, 2024, doi: 10.33050/italic.v2i2.554.

[2] A. Kristian, T. S. Goh, A. Ramadan, A. Erica, and S. V. Sihotang, "Application of AI in Optimizing Energy and Resource Management: Effectiveness of Deep Learning Models," *International Transactions on Artificial Intelligence (ITALIC)*, vol. 2, no. 2, pp. 99–105, 2024, doi: 10.33050/italic.v2i2.530.

[3] O. C. Agomuo, O. W. B. Jnr, and J. H. Muzamal, "Energy-Aware AI-based Optimal Cloud Infra Allocation for Provisioning of Resources," *27th IEEE/ACIS International Summer Conference on Software Engineering Artificial Intelligence Networking and Parallel/Distributed Computing, SNPD 2024 - Proceedings*, 2024, pp. 269–274, doi: 10.1109/SNPD61259.2024.10673918.

[4] S. K. Jha, J. Bilalovic, A. Jha, N. Patel, and H. Zhang, "Renewable energy: Present research and future scope of Artificial Intelligence," *Renewable and Sustainable Energy Reviews*, vol. 77, pp. 297–317, 2017, doi: 10.1016/j.rser.2017.04.018.

[5] A. Rashid, P. Biswas, A. Biswas, M. A. Al Nasim, K. D. Gupta, and R. George, "Present and Future of AI in Renewable Energy Domain : A Comprehensive Survey," *arXiv*, 2024, doi: 10.48550/arXiv.2406.16965.

[6] P. Boza and T. Evgeniou, "Artificial intelligence to support the integration of variable renewable energy sources to the power system," *Applied Energy*, vol. 290, 2021, doi: 10.1016/j.apenergy.2021.116754.

[7] A. Bennagi, O. A. Housrya, D. T. Cotfas, and P. A. Cotfas, "Comprehensive study of the artificial intelligence applied in renewable energy," *Energy Strategy Reviews*, vol. 54, 2024, doi: 10.1016/j.esr.2024.101446.

[8] U. Rusilowati, H. R. Ngemba, R. W. Anugrah, A. Fitriani, and E. D. Astuti, "Leveraging AI for Superior Efficiency in Energy Use and Development of Renewable Resources such as Solar Energy, Wind, and Bioenergy," *International Transactions on Artificial Intelligence (ITALIC)*, vol. 2, no. 2, pp. 114–120, 2024, doi: 10.33050/italic.v2i2.537.

[9] T. Ahmad *et al.*, "Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities," *Journal of Cleaner Production*, vol. 289, p. 125834, Mar. 2021, doi: 10.1016/j.jclepro.2021.125834.

[10] A. K. Pandey, V. K. Jadoun, N. S. Jayalakshmi, and M. Singh, "Decentralization of renewable energy sources based optimum scheduling and management through a virtual power plant," *Environmental Research Communications*, vol. 6, no. 11, 2024, doi: 10.1088/2515-7620/ad9087.

[11] M. S. S. Danish, "AI in Energy: Overcoming Unforeseen Obstacles," *AI (Switzerland)*, vol. 4, no. 2, pp. 406–425, 2023, doi: 10.3390/ai4020022.

[12] L. Cheng and T. Yu, "A new generation of AI: A review and perspective on machine learning technologies applied to smart energy and electric power systems," *International Journal of Energy Research*, vol. 43, no. 6, pp. 1928–1973, 2019, doi: 10.1002/er.4333.

[13] N. M. Kumar *et al.*, "Distributed energy resources and the application of ai, iot, and blockchain in smart grids," *Energies*, vol. 13, no. 21, 2020, doi: 10.3390/en13215739.

[14] J. T. Dellosa and E. C. Palconit, "Artificial Intelligence (AI) in Renewable Energy Systems: A Condensed Review of its Applications and Techniques," *21st IEEE International Conference on Environment and Electrical Engineering and 2021 5th IEEE Industrial and Commercial Power System Europe, EEEIC / I and CPS Europe 2021 - Proceedings*, 2021, doi: 10.1109/EEEIC/ICPSEurope51590.2021.9584587.

[15] G. Rathi and M. K. Soni, "Impact Analysis of PM KUSUM Scheme Individual Pump Solar Component C," in *2024 International Conference on Sustainable Energy: Energy Transition and Net-Zero Climate Future (ICUE)*, 2024, pp. 1-7, doi: 10.1109/ICUE63019.2024.10795592.

[16] "Enerdata," *Share of renewables in electricity production*, [Online]. Available: https://yearbook.enerdata.net/renewables/renewable-in-electricity-production-share.html. (Accessed: Feb. 10, 2025).

[17] J. A. Faraj, E. Popovici, and P. Leahy, "Solar Irradiance Database Comparison for PV System Design: A Case Study," *Sustainability (Switzerland)*, vol. 16, no. 15, 2024, doi: 10.3390/su16156436.

[18] S. Onwusinkwue *et al.*, "Artificial intelligence (AI) in renewable energy: A review of predictive maintenance and energy optimization," *World Journal of Advanced Research and Reviews*, vol. 21, no. 1, pp. 2487–2799, 2024, doi: 10.30574/wjarr.2024.21.1.0347.

[19] M. Huang, W. Liu, T. Wang, H. Song, X. Li, and A. Liu, "A queuing delay utilization scheme for on-path service aggregation in services-oriented computing networks," *IEEE Access*, vol. 7, pp. 23816–23833, 2019, doi: 10.1109/ACCESS.2019.2899402.

[20] Z. A. Khan, T. Hussain, I. U. Haq, F. U. M. Ullah, and S. W. Baik, "Towards efficient and effective renewable energy prediction via deep learning," *Energy Reports*, vol. 8, pp. 10230–10243, 2022, doi: 10.1016/j.egyr.2022.08.009.
[21] D. B. Unsal, A. Aksoz, S. Oyucu, J. M. Guerrero, and M. Guler, "A Comparative Study of AI Methods on Renewable Energy Prediction for Smart Grids: Case of Turkey," *Sustainability (Switzerland)* , vol. 16, no. 7, 2024, doi: 10.3390/su16072894.
[22] T. D. Makanju, T. Shongwe, and O. J. Famoriji, "Machine Learning Approaches for Power System Parameters Prediction: A Systematic Review," *IEEE Access*, vol. 12, pp. 66646–66679, 2024, doi: 10.1109/ACCESS.2024.3397676.
[23] A. A. Hassan and D. M. Atia, "Optimizing microgrid integration of renewable energy for sustainable solutions in off/on-grid communities," *Journal of Electrical Systems and Information Technology*, vol. 11, no. 1, 2024, doi: 10.1186/s43067-024-00186-6.
[24] A. K. Pandey, C. Mansour, K. K. Nandini, V. K. Jadoun, and N. S. Jayalakshmi, "A Golden Jackal based optimal operation and optimization of a virtual power plant involving renewable resources," *Scientific Reports*, vol. 15, no. 1, 2025, doi: 10.1038/s41598-025-09164-y.
[25] A. Abbass, "Hybrid renewable energy microgrid optimization: an analysis of system performance and cost-efficiency using Python-generated custom code for Diesel-wind-solar configurations," *Energy Storage and Saving*, 2025, doi: 10.1016/j.enss.2025.07.001.
[26] S. Wang and H. Zhang, "Inter-organizational cooperation in digital green supply chains: A catalyst for eco-innovations and sustainable business practices," *Journal of Cleaner Production*, vol. 472, 2024, doi: 10.1016/j.jclepro.2024.143383.
[27] S. Wang and H. Zhang, "Digital Transformation and Innovation Performance in Small- and Medium-Sized Enterprises: A Systems Perspective on the Interplay of Digital Adoption, Digital Drive, and Digital Culture," *Systems*, vol. 13, no. 1, 2025, doi: 10.3390/systems13010043.
[28] S. Wang and H. Zhang, "Artificial intelligence digital employees and sustainable innovation in online retail: The mediating role of ambidextrous green innovation and the moderating role of ethical anxiety," *Journal of Retailing and Consumer Services*, vol. 84, 2025, doi: 10.1016/j.jretconser.2025.104235.

BIOGRAPHIES OF AUTHORS

Dr. Nandini K. Krishnamurthy Member, IEEE received her B.E. degree in Electrical and Electronics Engineering from UBDT College of Engineering, Davangere, India and M.Tech. in Energy Systems Engineering from NMAMIT, Nitte, Karnataka, India. She received her Ph.D. degree from the Department of Electrical and Electronics Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education, India. Presently, she is working as an Assistant Professor Gd III in the Department of Electrical and Electronics Engineering, NMAM Institute of Technology, Nitte (Deemed to be University), India. Also, she is a member of IEEE, PES, and Young Professional, Women in Engineering (WiE) and lifetime member of the Institute of Engineers, India and AMIEE. Her research interests include electric vehicles and their charging infrastructure, power quality and mitigation, and integration of renewables into the grid. She can be contacted at email: nandini.kk@nitte.edu.in.

Dr. Anubhav Kumar Pandey Member, IEEE and Life Member AMIEE is currently working as an Assistant Professor in the Department of Electrical and Electronics Engineering, Dayananda Sagar College of Engineering, Dayananda Sagar Institutions, Karnataka, India. He has received a DST-sponsored INSPIRE Fellowship, Government of India, to conduct his doctoral research work at MIT Manipal. Earlier, he received an M.Tech. in Energy Technology in the year 2019 from Birla Institute of Technology Mesra, India. He has also earned a PGDC in Transmission and Distribution from the National Power Training Institute, NER, Ministry of Power, Government of India, in 2015 and a B.E. in EEE from BIT Raipur in 2014. His areas of research include, but are not limited to, modern power systems operation and control, virtual power plants, distributed generation systems, electric vehicles, energy management, soft computing, power markets, and sustainable energy systems. He has been associated with IEEE, PES, and Young Professional for the past five years as a professional member and also a Life Member of AMIEE. So far, he has published various SCIE papers in peer-reviewed Journals, Q1 and Q2 publications and actively performs review activities across reputed International Journals and premier Conferences. He can be contacted at email: anubhav01.bitmesra@gmail.com and anubhav-eee@dayanandasagar.edu.

Dr. Sumana Sreenivasa Rao has completed B.E. (EEE) from Sri Siddhartha Institute of Technology in 2005 and M. Tech (EC) from Sri Jagadguru Balagangadaranatha Institute of Technology (SJBIT) in the year 2013, respectively. Completed Ph.D. from Visveswaraya Technological University in the year of 2024. She has more than 15 years of experience in different engineering colleges. Presently working as an Assistant Professor in the EEE Department at Dayananda Sagar College of Engineering. She has many contributions in international and national journals, book chapters and Patents. She is also a Life Member of AMIEE. She can be contacted at email: sumana-eee@dayanandasagar.edu.