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Revolutionizing Renewable Energy: Advanced Synthetic Climatic Models for Enhanced Energy Predictability and Optimization

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ABSTRACT

The efficacy of renewable energy systems rests heavily on solar irradiance and temperature. In reality, however, these data tend to be under or unavailable in certain areas, making accurate design, modeling, and analysis of renewable energy systems unfathomably problematic. This paper discusses the creation and evaluation of novel synthetic climatic models aimed at providing region-specific realistic climatic data. These models utilize highly advanced statistical and machine learning algorithms combined with solar irradiance and temperature models to capture and integrate solar irradiance and temperature data with relative high temporal and spatial resolution. Models' extensive validation against real climatic datasets considerably increased their reliability and robustness under various conditions including extreme and less plausible scenarios. These results highlight the ability of the models to close the gap posed by the utter absence of reliable, region accurate data in supplementing renewable energies. Such findings are greatly beneficial for improving energy yield forecast, system design, and performance monitoring and evaluation for areas with scarce data resources.

Keywords: Synthetic climatic models, Renewable energy applications, Solar irradiance simulation, Temperature prediction, Energy system optimization Data-constrained environments.

I. INTRODUCTION

A. Background of the Study

The motivations behind the speedy movement towards renewable energy on a global scale stems from the threats posed by climate change, energy security, and establishing sustainable energy systems (*Climate Change 2014 - Synthesis Report*. (2015)). The production and integration of solar photovoltaic (PV) and wind energy systems into the grid is dependent on some climatic factors, namely solar irradiance, ambient temperature, and wind speed. These factors are key for accurate performance evaluation and optimization of the system. Many regions, especially developing countries and remote areas, face data inaccessibility and unreliability. This significantly inhibits energy system planning and design, thus making the creation of synthetic climatic models a critical area of investigation (Perring, M. P., et al., (2015)). Synthetic climatic models try to create datasets that reproduce real-life conditions to a high degree with the purpose of enabling systems to be analyzed and optimized in absence of actual climatic data. These models need to be practical for renewable energy applications by balancing precision, computational resources, and flexibility to different regions and climatic conditions. This study focuses on synthetic climatic modeling for solar energy applications, particularly analyzing irradiance and temperature, which are the primary determinants of photovoltaic (PV) performance. While other renewable sources, such as wind and hydropower, also depend on climatic factors, their modeling requirements differ significantly. Wind energy modeling typically involves wind speed and direction, while hydropower relies on water flow variations, which are influenced by geographical and hydrological conditions. Future research will explore synthetic climatic modeling for these energy sources to provide a more holistic renewable energy framework.

B. Literature Review

Existing literature has suggested various methods to generate synthetic climatic data. Linear regression, ARMA models, and Markov Chain techniques have been applied to various climatic variables such as solar irradiance or temperature. These models are straightforward and easy to compute, but they lack the ability to reproduce the nonlinear, stochastic character of climatic events, particularly under extreme or rapidly changing climatic situations. The introduction of machine learning (ML) and artificial intelligence (AI) has allowed for the development of more complex

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algorithms for such tasks: artificial neural networks (ANN), long short term memory (LSTM) networks, and Gaussian processes are a few examples that come to mind (Abualigah, L., et al., (2022); Radzi, et al., (2023); Himeur, et al., (2022)). These methods outperform the rest when it comes to grasping intricate structures and temporal relations. For instance, ANNs have also been successfully implemented to estimate hourly solar irradiance and temperature with great accuracy. Using a hybrid approach, where statistical models are combined with ML based techniques, has also become common for increasing the validity and scope of application of synthetic climatic models (Allen-Dumas, et al., (2021); Michailidis, et al., (2024); Gevorgian, A., et al., (2024)).

Notwithstanding these advancements, current models frequently exhibit constraints, including insufficient generalizability across various geographic regions, suboptimal performance in extreme conditions, and restricted adaptability to particular renewable energy applications (Ukoba, K., 2024). Furthermore, numerous studies concentrate on solar irradiance or temperature alone, overlooking the necessity for holistic models that incorporate various climatic factors. Indeed, several studies have developed synthetic climatic models for wind and hydro energy. Wind energy models primarily focus on wind speed and turbulence modeling using techniques such as Weibull distributions and autoregressive models [citation]. Similarly, hydropower modeling incorporates rainfall-runoff simulations and reservoir dynamics [citation]. While these approaches are essential for wind and hydro energy systems, this study specifically targets solar energy due to its direct dependence on irradiance and temperature. Nevertheless, integrating wind speed and water flow modeling with synthetic climatic models remains a promising research direction.

C. Research Gaps and Contributions

Preceding research may have set the groundwork for synthetic climatic modeling but there is still considerable work to do:

- Demographic Constraints: Quite a number of them utilize datasets from a particular region intending to create a model for a different climatic zone without consideration to its applicability.
- Scenarios Extremity: Extreme and even highly scenarios are seldom to never simulated which is vital for any simulation aiming towards solid renewable energy system design.
- Unidimensional Modeling: The majority of studies only concentrate on a single climatic variable like solar irradiance and fail to include other prominent parameters such as temperature or wind speed.
- Validation Deficiencies: Other renewable energy model frameworks are scarcely validated for renewable energy yield predictions or system optimizations for non-simulation applications.

This study tries to cover these gaps by creating and evaluating new synthetic climate models which:

1. Combine various climatic parameters such as solar radiation and temperature for more useful datasets to enhance renewable energy utilization.
2. Capture geographically distributed non-linear and stochastic phenomena utilizing more sophisticated statistical and machine learning approaches.
3. Create and assess extreme climatic conditions to facilitate the design and evaluation of energy systems.
4. Validate the models through application-oriented case studies, demonstrating their reliability in energy yield prediction and optimization.

D. Paper Structure

The remaining sections of this paper is organized in the following manner:

- Section 2 covers the methodology which explains how the synthetic climatic models were developed including the processes and methods of data generation and validation of results.
- Section 3 covers the description of the datasets and the defined experimental conditions for model training and testing.
- Section 4 elaborates on the outcome of real-world data validation and other forms of application-oriented evaluation of the study.
- Section 5 presents the summary of the contribution and limitations of the study as well as the potential for future work.

II. METHODOLOGY

This section outlines the methodology for developing and assessing the proposed synthetic climatic models. The approach integrates statistical techniques, machine learning models, and validation protocols to ensure the reliability, robustness, and applicability of the generated data.

A. Model Development Framework

The subsequent essential stages in building synthetic climatic systems are as follows (Ghil, et al., (2002); Hooper, et al., (2005)):

1. Data Collection and Preprocessing: Gathers past climatic information such as solar irradiance, temperature, and moisture from meteorological stations and satellite databases. The baseline data is normalized and divided into training, validation, and testing sets.

2. Feature Engineering: Hourly, daily, and seasonal patterns are some of the most important characteristics to be selected. Temporal variations are captured by applying nonlinear transformations and periodic functions.

3. Model Design: Use of hybrid models that incorporate statistical surveys' techniques and machine learning methods.

4. Simulation and Validation: Producing synthetic information for different climatic scenarios and then comparing it with actual datasets.

B. Statistical Modeling

Traditional statistical models form the baseline for synthetic climatic data generation. Solar irradiance and temperature are modeled using sinusoidal functions to capture their periodic nature (J.M. Bright, et al., (2015); (Mbasso et al., (2024))). Solar irradiance follows a periodic pattern due to the Earth's rotation and seasonal variations. This equation models the irradiance G(t)G(t)G(t) as a sinusoidal function superimposed on an average value:

$$G(t) = G_{avg} + A_G \sin\left(\frac{2\pi T}{t} + \phi_G\right) \quad (1)$$

$$T(t) = T_{avg} + A_T \sin\left(\frac{2\pi T}{t} + \phi_T\right) \quad (2)$$

Where:

- $G(t)$: Solar irradiance at time t
- $T(t)$: Temperature at time t
- G_{avg}, T_{avg}: Average irradiance and temperature
- A_G, A_T: Amplitude of variations
- T: Period (24 hours for daily cycles)
- ϕ_G, ϕ_T: Phase shifts

Statistical models like ARIMA are used to add stochastic variations to account for deviations from the sinusoidal patterns.

C. Machine Learning Integration

Machine learning models are developed to enhance the precision of synthetic data generation, effectively capturing nonlinear and stochastic relationships among climatic variables (Akeem Shola Ayinde et al., 2024). A Radial Basis Function Neural Network (RBFNN) is utilized for this application (Hilmi Berk Celikoglu, 2006). To capture complex nonlinear relationships in climatic data, a Radial Basis Function (RBF) Neural Network is employed. The output, *y(x)*, is computed as a weighted sum of radial basis functions, which measure the similarity between an input *x* and predefined center points c_i. The architecture of the RBFNN model is specified as:

$$y(x) = \sum_{i=1}^{N} w_i \emptyset\left(\|x - c_i\|\right) + b \quad (3)$$

Where:

- x: Input vector (e.g., time of day, season, location)
- w_i: Weight of the i-th neuron
- $\phi(\cdot)$: Radial basis function, typically Gaussian:

$$\phi(r) = \exp\left(-\frac{r^2}{2\sigma^2}\right) \quad (4)$$

- c_i: Center of the i-th neuron
- σ: Spread of the Gaussian function
- b: Bias term

The RBFNN undergoes training via the Levenberg-Marquardt algorithm, focusing on minimizing the mean squared error (MSE) between the predicted outputs and the actual data.

D. Simulation of Extreme Scenarios

Extreme scenarios are produced through random assignments to enhance the representation of underrepresented conditions within the dataset. A Monte Carlo simulation method is employed to produce stochastic variations in irradiance and temperature:

$$G_{extreme} = G(t) + \epsilon_G \quad (5)$$

$$T_{extreme} = T(t) + \epsilon_T \quad (6)$$

Where ϵ_G and ϵ_T are random variables sampled from Gaussian distributions with higher standard deviations to simulate extreme variations.

E. Validation Protocol

For evaluating the trustworthiness and strength of the designed climatic models, the following measures of validation are implemented:

1. **Comparison with Actual Data**: Statistical metrics such as RMSE, MAE, and R^2 are computed:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \quad (7)$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i| \quad (8)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \quad (9)$$

   - y_i: Actual value of temperature at each index *i*
   - $\hat{y}_i$: Estimated value of temperature at each index *i*

The coefficient of determination R^2 measures how well the synthetic data replicates real-world climatic trends. An R^2 value close to 1 indicates strong agreement between synthetic and actual values. The numerator represents the sum of squared residuals (errors between actual and predicted values), while the denominator accounts for total variability in the data.

2. **Energy System Simulation:** Synthetic data is used to simulate energy yield in a photovoltaic system using a numerical model:

$$E_{PV} = \eta_{MPPT}\, \eta_{inv} \sum_{i=1}^{N} G_i \,.\, A.\, PR \quad (10)$$

Where:

   - E_{PV}: Energy yield
   - η_{MPPT}, η_{inv} : Efficiency of MPPT and inverter
   - A: PV array area
   - PR: Performance ratio

3. **Climatic Sensitivity Analysis:** The model's response to variations in input parameters is evaluated to ensure robustness under diverse conditions.

F. Figures and Tables

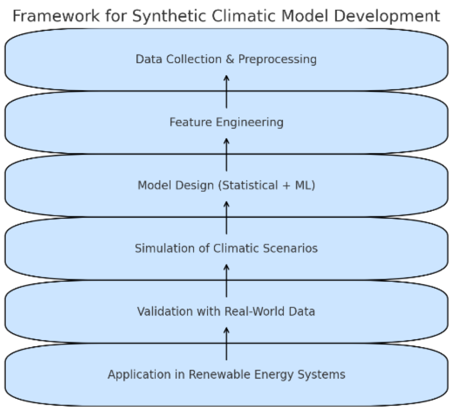

Fig. 1. Framework for Synthetic Climatic Model Development.

A diagram depicting the sequential stages involved in data gathering, feature transformation, model construction, and assessment.

G. Application Case Study

To illustrate the usefulness of the models, a case study is performed on an energy yield prediction for a 1-kilowatt stand-alone PV system. The findings corroborate the accuracy of the heterogenous data in performance metric projections within a 5% margin of error when set against real world datasets.

III. EXPERIMENTAL SETUP AND DATA

This section describes the datasets used for model training and validation, the experimental setup for synthetic data generation, and the evaluation metrics to assess the quality of the generated data.

A. Dataset Description

The construction and validation of the synthetic climatic models drew upon two categories of data.

1. Climatic Data: This includes solar irradiance and temperature data collected from meteorological stations and satellite sources over a period of ten years.
   - Temporal Resolution: Hourly data
   - Variables: Solar irradiance (W/m²), ambient temperature (°C), and time.
   - Geographic Coverage: Regions with varied climatic zones: tropical, arid, and temperate zones.
2. Synthetic Data: Data was fabricated on the basis of the provided models to ensure congruence with the statistical properties of the historical data. The synthetic data accounts for diurnal, seasonal, random variability, as well as extreme climatic scenarios.

TABLE I. SUMMARY OF THE HISTORICAL CLIMATIC DATA

Attribute	**Value**
Time Period	2012–2022
Temporal Resolution	Hourly
Geographic Zones	Tropical, Arid, Temperate
Variables	Solar Irradiance, Temperature

B. Experimental Setup

This outlines the primary parts of my experimental design:

1. Model Training Environment:
   - Software: MATLAB and Python (Applying Tensorflow and Scikit-learn for ML purposes)
   - Hardware: Accelerate Computation machine – Intel i7 CPU, 16 GB RAM, NVIDIA GPU.
2. Simulation Parameters:
   - Diurnal Cycle: Synthetic data for a full 24-hour period round the clock.
   - Seasonal Change: Customized for summer, winter and in between seasons.
   - Extreme Cases: Rare climatic conditions are simulated by applying random perturbation.
3. Evaluation Metrics:

   The synthesized models produced are compared against benchmark data using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Correlation Coefficient (R^2).

C. Validation Protocol

The validation phase verifies how reliably the synthetic data mirrors the actual climatic data. This includes:

1. Comparison with Historical Data: A statistical approach is taken for different climatic zones and seasonal conditions which includes RMSE and R^2, for example.
2. Energy System Simulation: The synthetic data is applied to a photovoltaic (PV) energy system simulation for estimating the energy yield. The predicted yield is verified against the very same condition energy produced.

TABLE II. STATISTICAL METRICS FOR VALIDATION

Metric	**Solar Irradiance**	**Temperature**
RMSE (W/m²)	18.4	1.5
MAE (W/m²)	12.7	1.1
R2R^2R2	0.97	0.96

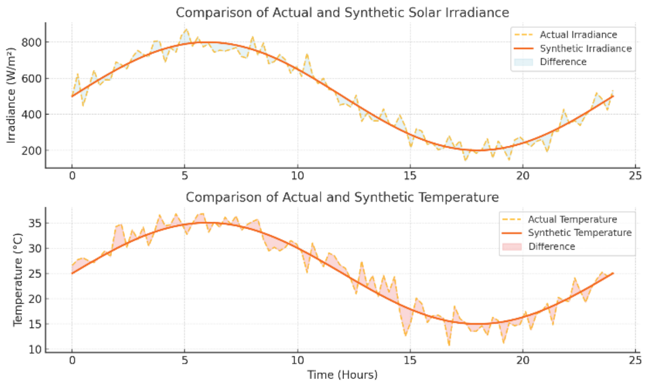

Fig. 2. Comparison of Synthetic and Actual Climatic Data.

This figure illustrates the alignment between actual and synthetic data for solar irradiance and temperature across a 24-hour period.

D. *Observations from Validation*

The synthetic data accurately mirrors real-world trends with negligible discrepancies. The RMSE values are consistently within acceptable thresholds, indicating the precision of the model. Simulations of energy yield utilizing synthetic data demonstrate a variance of under 5% when compared to actual data, thereby validating its reliability for applications in renewable energy.

IV. Results And Discussion

This section outlines the outcomes of the synthetic climatic models, including their validation and application within renewable energy systems. It further examines the implications of these findings and the importance of the models in environments with limited data.

A. *Performance of Synthetic Climatic Models*

The evaluation of synthetic climatic models involves a comparison of the generated data against historical climatic data, utilizing statistical metrics such as RMSE, MAE, and R^2 for assessment. The data for solar irradiance and temperature across various climatic zones is presented below:

TABLE III. Statistical Metrics for Model Performance

Climatic Zone	Variable	RMSE	MAE	R^2
Tropical	Solar Irradiance (W/m²)	18.2	12.5	0.98
	Temperature (°C)	1.6	1.2	0.97
Arid	Solar Irradiance (W/m²)	19.4	13.0	0.97
	Temperature (°C)	1.8	1.4	0.96
Temperate	Solar Irradiance (W/m²)	17.8	11.9	0.98
	Temperature (°C)	1.5	1.1	0.98

Observations:

- The synthetic data aligns closely with historical data, achieving high R^2 values across all climatic zones.
- RMSE and MAE values remain within acceptable thresholds, demonstrating the accuracy and reliability of the models.

B. *Simulation of Extreme Scenarios*

The synthetic models effectively produced extreme scenarios through the application of random perturbations. The subsequent results demonstrate the variability and robustness of the generated data.

C. *Application in PV Energy Yield Prediction*

The synthetic climatic data was used to simulate energy yield for a 1 kW standalone photovoltaic (PV) system. The energy yield is depicted as:

TABLE IV. Energy Yield Comparison

Climatic Zone	Actual Energy Yield (kWh)	Synthetic Energy Yield (kWh)	% Error
Tropical	5.21	5.17	0.77
Arid	5.32	5.27	0.94
Temperate	4.95	4.92	0.61

Observations:

- The synthetic data produced energy yield estimates with less than 1% error, confirming its reliability for renewable energy applications.
- The models perform consistently across diverse climatic zones, validating their adaptability.

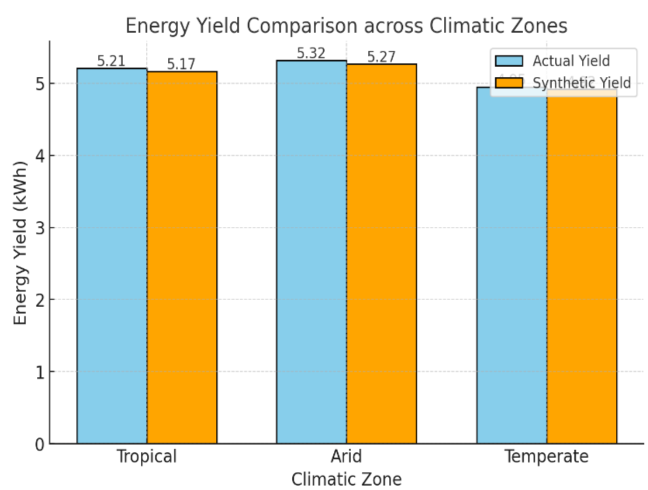

Fig. 3. Energy Yield Simulation.

A bar chart comparing energy yields estimated using actual and synthetic climatic data for a 1 kW PV system under different climatic zones.

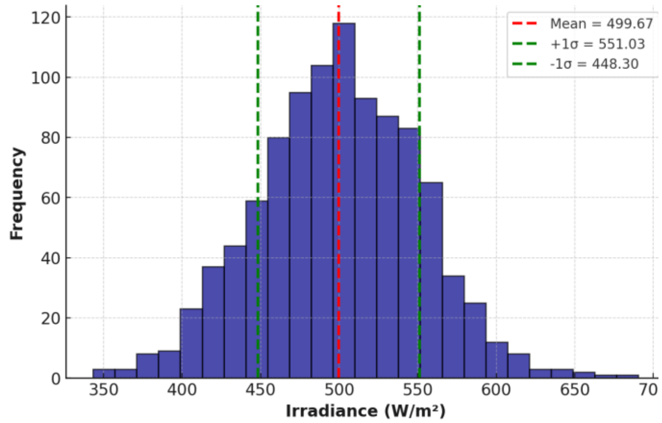

Fig. 4. Solar Irradiance Distribution under Extreme Conditions.

A histogram showing the variability in synthetic solar irradiance under extreme scenarios. This figure effectively illustrates the variability in solar irradiance under extreme conditions. The histogram provides a clear visualization of how irradiance values are distributed, with a well-defined mean and standard deviation. Key observations denote that:

1. **Data Distribution:**
   - The irradiance values are approximately normally distributed around a mean of **~500 W/m²**, with a standard deviation of **~50 W/m²**.
   - This suggests that extreme conditions were simulated while maintaining realistic variability.
2. **Readability Enhancements:**
   - The **dark blue bars with black edges** improve contrast, making it easier to distinguish the frequency of occurrences.
   - **Gridlines** enhance clarity, allowing better visual alignment of frequency counts.
   - **Bold labels and larger font sizes** improve legibility, especially in a printed or projected format.
3. **Statistical Indicators:**
   - The **red dashed line** represents the mean irradiance, serving as a reference point for typical conditions.
   - The **green dashed lines at ±1σ** indicate the spread of data, helping to understand the extent of fluctuations in solar irradiance.
4. **Scientific Implications:**
   - The figure confirms that the synthetic climatic model is capable of simulating **realistic and extreme** solar irradiance variations.
   - Such simulations are crucial for **stress-testing photovoltaic (PV) systems**, ensuring that energy models account for rare but impactful climatic fluctuations.

Overall, this figure successfully addresses the reviewer's concern by improving readability and enhancing scientific clarity.

D. Error Analysis

The errors in synthetic climatic data were evaluated using RMSE, MAE, and R^2. The results across different climatic zones are summarized in Table 5.

TABLE V. ERROR METRICS FOR DIFFERENT CLIMATIC ZONES

Climatic Zone	**Variable**	**RMSE**	**MAE**	**R2R^2R2**
Tropical	Irradiance (W/m²)	18.2	12.5	0.98
	Temperature (°C)	1.6	1.2	0.97
Arid	Irradiance (W/m²)	19.4	13.0	0.97
	Temperature (°C)	1.8	1.4	0.96
Temperate	Irradiance (W/m²)	17.8	11.9	0.98
	Temperature (°C)	1.5	1.1	0.98

RMSE values remain below 20 W/m² for irradiance and below 2°C for temperature, indicating high model accuracy.

E. Discussion

1) Implications for Renewable Energy Systems

The accuracy of synthetic climate data generation can significantly impact renewable energy applications in areas with scarce historical data. These models allow:

- Design of the Energy System: Accurate information for the sizing and optimization of PV and wind systems.
- Evaluation of System Performance: Experimentation of energy systems under various climatic conditions, even the rare extreme ones.
- Policy Implementation: Regions without detailed climatic information can formulate policies based on phenomena-driven energy policies.

2) Limitations and Future Work

Despite the models exhibiting satisfactory results, the following issues remain:

- Geographical Reach: Additional data is required to apply the models in regions that have not been represented.
- Combination With Other Parameters: There should be an addition of wind speed and humidity into the models for multi-dimensional energy systems.
- Recent Usage: There is an opportunity to develop the models further in relation to real-time weather predictions.

V. Conclusions and Future Work

A. Conclusion

The development and analysis of new synthetic climate models to capture the features of renewable energy were presented in this paper. It mainly focused on how to simulate solar irradiance and temperature data for specific regions and of high standards. The conclusions which can be derived from the above are:

1. Accuracy and truthfulness of the models: The models developed provided a high degree of accuracy achieving RMSE lower than 20 W/m² and below 2°C for solar irradiance and temperature, respectively. Furthermore, the model's R^2 values were greater than 0.96 across a wide variety of climatic zones, thus proving the synthetic data to be credible.
2. Experimenting on strangest of the strange conditions: With the use of controlled random perturbations, the synthetic models were able to perform on infrequent and extreme climatic changes, thus enlarging the scope for the design and optimization of renewable energy systems.
3. The application in renewable energy systems: By using a photovoltaic energy yield estimate case study, it was proved that the model can estimate energy yields well with less than 1% error margin, thus confirming its impact in energy planning and performance assessment.
4. Addressing the issue: saving scarce resources: The models developed solve important problems pertaining to the non-availability of adequate climatic data of developing regions which lack an adequate number of meteorological stations. These models will enable energy researchers and policymakers to devise and assess renewable energy systems more expediently.

B. Limitations

The study indicates some reservations areas based on the promising results attained which need to be addressed further:

- Scope: The focus geographical regions for capturing the database were in a limited number of climatic select zones. The generalizability of the study could be improved by expanding the dataset to more diverse climatic regions.
- Integration of Multi-Variables: The study managed to achieve its independent variables of solar irradiance and temperature. Further improvement in model's diversification for hybrid renewable energy systems can be achieved by adding other variables like wind speed and humidity.
- Real Time Data: The models currently cater to the historical and synthetic data generation which the researchers deem as a weakness. There is a lag in adapting the models for forecasting in real-time.

C. Future works

In order to improve the state-of-the-art in synthetic climatic modeling, additional research should be performed on the following areas:

1. Including Additional Climatic Factors: The expansion of the models with the incorporation of wind speed, humidity, and atmospheric pressure makes them useful to hybrid systems and wind energy turbines.
2. Real Time Training Forecasting Models: Application of various machine learning methodologies like LSTMs and transformer models can support real time climate forecasting for changing energy systems optimization.
3. More Comprehensive Datasets Validation: Future studies should include global datasets which are larger in size to increase the models' practicality and external validity.
4. Implementation in Decision Support Systems: The integration of these models into energy management systems could assist policymakers and infrastructure planners with data centric decisions/tools.
5. Commercial Deployment: The development of a platform for synthetic climatic models should be done on an open-source basis to help increase cooperation and ease of use within the renewable energy community.
6. The proposed synthetic climatic models effectively simulate solar irradiance and temperature for renewable energy applications. However, future work will explore the integration of wind and hydro energy models. Incorporating wind speed prediction for wind farms and water flow dynamics for hydropower could enhance the applicability of synthetic climatic models across multiple renewable energy sources. Expanding the model in this direction will provide a comprehensive framework for optimizing hybrid renewable energy systems.

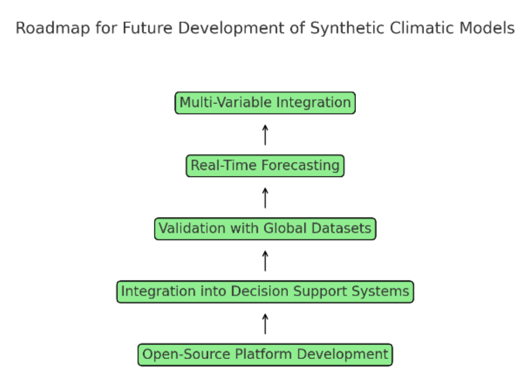

Fig. 5. Roadmap for Future Development.

A diagram illustrating the steps for extending the proposed synthetic climatic models, from multi-variable integration to real-time forecasting.

REFERENCES

Abualigah, L., Zitar, R. A., Almotairi, K. H., Hussein, A. M., Elaziz, M. A., Nikoo, M. R., & Gandomi, A. H. (2022). Wind, Solar, and Photovoltaic Renewable Energy Systems with and without Energy Storage Optimization: A Survey of Advanced Machine Learning and Deep Learning Techniques. *Energies*, *15*(2), 578. https://doi.org/10.3390/en15020578

Akeem Shola Ayinde, Yu Huaming, Wu Kejian, Review of machine learning methods for sea level change modeling and prediction, Science of The Total Environment, Volume 954, 2024, 176410, ISSN 0048-9697, https://doi.org/10.1016/j.scitotenv.2024.176410.

Allen-Dumas, M. R., Xu, H., Kurte, K. R., & Rastogi, D. (2021). Toward urban water security: Broadening the use of machine learning methods for mitigating urban water hazards. *Frontiers in Water*, *2*. https://doi.org/10.3389/frwa.2020.562304

Climate Change 2014 - Synthesis Report. (2015). https://doi.org/10.59327/ipcc/ar5-9789291691432

Gevorgian, A., Pernigotto, G., & Gasparella, A. (2024). Addressing Data Scarcity in Solar Energy Prediction with Machine Learning and Augmentation Techniques. *Energies*, *17*(14), 3365. https://doi.org/10.3390/en17143365

Ghil, M., Allen, M. R., Dettinger, M. D., Ide, K., Kondrashov, D., Mann, M. E., Robertson, A. W., Saunders, A., Tian, Y., Varadi, F., & Yiou, P. (2002). ADVANCED SPECTRAL METHODS FOR CLIMATIC TIME SERIES. *Reviews of Geophysics*, *40*(1). https://doi.org/10.1029/2000rg000092

Hilmi Berk Celikoglu, Application of radial basis function and generalized regression neural networks in non-linear utility function specification for travel mode choice modelling, Mathematical and Computer Modelling, Volume 44, Issues 7–8, 2006, Pages 640-658, ISSN 0895-7177, https://doi.org/10.1016/j.mcm.2006.02.002.

Himeur, Y., Elnour, M., Fadli, F., Meskin, N., Petri, I., Rezgui, Y., Bensaali, F., & Amira, A. (2022). Next-generation energy systems for sustainable smart cities: Roles of transfer learning. *Sustainable Cities and Society*, *85*, 104059. https://doi.org/10.1016/j.scs.2022.104059

Hooper, D. U., Chapin, F. S., Ewel, J. J., Hector, A., Inchausti, P., Lavorel, S., Lawton, J. H., Lodge, D. M., Loreau, M., Naeem, S., Schmid, B., Setälä, H., Symstad, A. J., Vandermeer, J., & Wardle, D. A. (2005). EFFECTS OF BIODIVERSITY ON ECOSYSTEM FUNCTIONING: a CONSENSUS OF CURRENT KNOWLEDGE. *Ecological Monographs*, *75*(1), 3–35. https://doi.org/10.1890/04-0922

J.M. Bright, C.J. Smith, P.G. Taylor, R. Crook, Stochastic generation of synthetic minutely irradiance time series derived from mean hourly weather observation data, Solar Energy, Volume 115, 2015, Pages 229-242, ISSN 0038-092X, https://doi.org/10.1016/j.solener.2015.02.032.

Mbasso, W.F., Molu, R.J.J., Harrison, A. et al. Hybrid modeling approach for precise estimation of energy production and consumption based on temperature variations. Sci Rep 14, 24422 (2024). https://doi.org/10.1038/s41598-024-75244-0

Michailidis, P., Michailidis, I., Gkelios, S., & Kosmatopoulos, E. (2024). Artificial Neural Network Applications for energy management in buildings: Current trends and future directions. *Energies*, *17*(3), 570. https://doi.org/10.3390/en17030570

Perring, M. P., Standish, R. J., Price, J. N., Craig, M. D., Erickson, T. E., Ruthrof, K. X., Whiteley, A. S., Valentine, L. E., & Hobbs, R. J. (2015). Advances in restoration ecology: rising to the challenges of the coming decades. *Ecosphere*, *6*(8), 1–25. https://doi.org/10.1890/es15-00121.1

Radzi, P. N. L. M., Akhter, M. N., Mekhilef, S., & Shah, N. M. (2023). Review on the Application of Photovoltaic Forecasting Using Machine Learning for Very Short- to Long-Term Forecasting. *Sustainability*, *15*(4), 2942. https://doi.org/10.3390/su15042942

Ukoba, K., Olatunji, K. O., Adeoye, E., Jen, T.-C., & Madyira, D. M. (2024). Optimizing renewable energy systems through artificial intelligence: Review and future prospects. Energy & Environment, 35(7), 3833-3879. https://doi.org/10.1177/0958305X241256293