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Article

Physics-Informed AI-Driven Digital Twin Framework for Renewable Energy Forecasting and Real-Time Power Grid Integration

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Abstract: The current study proposes an innovative physics-informed AI-driven digital twin methodology, which is expected to improve the forecasting of renewable energy generation and allow for the safe, flexible, and efficient integration of renewable sources in modern power grids. The suggested framework integrates the knowledge of artificial intelligence and physical principles that can be helpful in overcoming the challenges associated with the variable nature of renewable generation, especially that of solar and wind sources, whose operation is heavily dependent on the surrounding environment. Secondary research and exploratory data analysis performed using a large time-series dataset allowed for identifying patterns in the temporal generation of renewables, correlation between renewables and environmental parameters, dynamics of changes in the demand, behavior of batteries, and operational conditions of grids. It was found that there are substantial dependencies of renewable generation from environmental conditions, permanent imbalances between supply and demand, and an important function of battery systems in maintaining the resilience of grids. The review of literature confirmed the need for hybrid methodologies, which take into account both forecasting accuracy and physical consistency. Digital twin technology allows for representing the dynamic state of power grids.

Keywords: Physics-Informed AI, Digital Twin, Renewable Energy Forecasting, Power Grid Integration, Smart Grid

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1. Introduction

Artificial intelligence (AI) is increasingly used in renewable-energy systems to improve forecasting, resource assessment, monitoring, control, and grid integration. AI can support clean-energy transition by optimizing system design and energy use and by improving power-grid operation through predictive intelligence [1], [2]. The need for such capabilities is growing because solar and wind generation are strongly influenced by changing environmental conditions and therefore introduce variability into electricity supply.

The growing share of renewable power sources makes forecasting, grid stability, and operational decision-making more challenging because generation, electricity demand, energy

storage, electric-vehicle charging, and grid conditions interact continuously. Traditional forecasting can struggle to represent these dynamic relationships, while conventional digital simulation may lack predictive intelligence when physical system behavior is not sufficiently incorporated. These limitations motivate an integrated framework that combines AI-based prediction, physical principles, and a continuously updated digital representation of the power system.

Previous research shows that data-driven forecasting can capture complex renewable-energy patterns. Ukoba et al. [3] identify forecasting, resource assessment, monitoring and control, and grid integration as major AI applications, while Abdul Baseer et al. [4] report improved wind and solar prediction using ensemble learning relative to several individual architectures. Forecasting also becomes more valuable when it is linked to demand-side management, power scheduling, and demand response [5]. Heterogeneous inputs nevertheless create challenges in uncertainty, consistency, transparency, and operational reliability [6].

Physics-informed learning addresses part of this limitation by embedding governing relationships into data-driven models. Physics-informed neural networks have been applied to forecasting, state estimation, and system identification in power systems [7]. Bayesian physics-informed approaches can also represent uncertainty in inverter-dominated systems [8], while related methods have been applied to solar-thermal systems [9], power-system modeling [10], and electrolysis temperature prediction [11]. Their effectiveness nevertheless depends on the appropriateness of the embedded physical formulation and its ability to remain adaptable under changing operating conditions.

Digital twin technology provides a complementary mechanism for representing the evolving state of physical energy systems. Digital twins have been proposed for smart-grid monitoring, simulation, fault diagnosis, planning, and operational optimization, although interoperability, data management, synchronization, and computational complexity remain important challenges [12], [13]. Their role becomes more complex when renewable generation, storage, vehicle-to-grid resources, and cross-infrastructure coordination are considered [14], [15].

Renewable integration also requires real-time coordination supported by reliable sensing, communication, and intelligent control [16]. Intermittency, voltage and frequency control, power quality, and storage requirements remain central grid-integration challenges [17]. Advanced optimization, including deep reinforcement learning, has been explored for balancing multiple smart-grid objectives [18], while broader smart-grid research emphasizes the combined importance of AI, renewable integration, system interoperability, cybersecurity, and sustainable energy management [19].

Despite these advances, the literature discusses AI forecasting, physics-informed learning, and digital twins more often as separate or partially connected technologies. A coherent framework that combines predictive accuracy, physical consistency, real-time digital representation, uncertainty awareness, and grid decision support remains insufficiently addressed. The objective of this study is to develop a physics-informed AI-driven digital twin framework to enhance renewable-energy forecasting, support secure and flexible real-time power-grid integration, and strengthen grid resilience under renewable variability.

2. Materials and Methods

Research Design

In this research a mixed methodological approach is followed by a secondary research analysis combined with exploratory quantitative analysis of the potential of a Physics-Informed AI-Driven Digital Twin Framework for renewable energy forecasting and real-time integration with the power-grid. In the secondary research phase, journal articles, academic books, relevant research publications and trustworthy news articles have been used to determine known facts, technological advancement, challenges and practical issues of Artificial Intelligence, Physics-informed AI, Digital Twin, Renewable Energy Forecasting, and Smart-grid Management. The exploratory part is quantitative

analysis of the selected bqeb_data_v1.csv data in R Studio and R scripts. This module looks at the characteristics of electricity demand, grid operating characteristics, renewable generation, environmental characteristics, temporal patterns, and battery storage. The two approaches are complementary since the second approach is used to find out patterns in the data that can help interpret the results of the exploratory analysis, and the data-based approach is used to provide quantitative evidence for the research.

Secondary Research Analysis

Secondary research analysis was conducted to build up theoretical and contextual background of the study and to find evidence relevant to the research objectives. Academic journal articles were mainly reviewed for insights into recent advancements in renewable energy forecasting, physics-informed AI, applications of Digital Twins, decision-making in VARs, and integration with smart grids. Where relevant, academic books or research publications were also included that delivered existing theories and/or wider explanations of energy-system technologies. AI developments and applications for renewable-energy systems were presented through the use of credible news articles, while keeping the information up to date. The information gathered from these sources was not merely taken on face value as a piece of data but critically analyzed, taking into account technological capacity, practical issues, requirements for the system, as well as restrictions and limitations voiced by previous researchers. The results obtained by secondary sources then serve as a contextual basis for interpreting the results that have been obtained from the selected data.

Dataset Source and Description

The exploratory component is based on the bqeb_data_v1.csv data provided in CSV format that includes 10512 observations and 37 variables [20]. It is a 15-minute time series dataset from 1 Jan 2026 to 20 April 2026, spanning 12 nodes located in a single region (R1) and 876 observations per node [20]. There were no missing values found for the variables. The dataset contains data for various components of the research framework such as renewable generation (solar_mw, wind_mw, renewable_total_mw), environmental conditions (temp, humidity, wind_speed, solar_irradiance, and rain), and electricity demand (total, residential, commercial, and industrial load) [20]. In addition, battery state of charge, charging and discharging activity, and battery temperature, as well as grid indicators such as frequency, voltage, line losses, and outages. Other variables include electric vehicle activity, electricity prices, demand-response events, forecasting data and information, and indicators of system risk. The combination allows for the exploratory analysis of relationships between renewable resources, physical conditions, energy demand, storage, and grid operation.

Exploratory Data Analysis and Variable Classification

Exploratory Data Analysis was used to look at the structure, distribution, variability and relations in the selected set of data prior to interpretation of research results. The variables were categorized by their analytical properties, with the timestamp representing the time variable; region_id, node_id and attack_class were categorical variables; renewable generation, weather, demand, battery and grid measurements were continuous numeric variables. Peak tariff, demand-response events, outages, cyber alerts, and sensor faults were all included in binary indicators. The exploratory analysis included looking at the structure of the data, data completeness, descriptive characteristics of the data, temporal trend analysis, distribution analysis of variables, correlation analysis and analysis of relations between renewable generation and related physical conditions. Special emphasis was placed on examining the relationship between wind generation and wind speed and the relationship between solar generation and solar irradiance due to the possibility of finding empirical evidence for association between renewable generation and environmental properties. The node-level characteristics too were taken into account in order to be able to detect differences between the energy system behaviors in the 12 nodes under consideration.

R-Based Analytical and Visualization Procedure

The exploratory analysis was carried out with R, scripts in R Studio, so the procedures followed

and the visualization produced can be reproduced systematically. The analytical approach comprised importing the CSV data set, looking at the data type and structure of the variables, formatting the time stamp into a suitable date-time type, checking that observations were complete, computing descriptive statistics, building of relevant derived variables, analysis of relationships between the numerical variables and the production of graphical visualizations. The following two are special measures derived: Renewable penetration can be defined as the percentage of renewable generation in relation to electricity load, and a net energy balance would be defined as renewable generation minus electricity demand. These measures enable the analysis to take account of the availability of renewables in relation to system requirement, instead of looking at generation in isolation. Relationships between renewable energy generation, environmental parameters, demand, storage, and grid parameters are then explored using correlation analysis and graphical methods. The resulting visualizations are the empirical outputs presented and interpreted in the Results section.

Ethical Considerations

Ethical issues have been considered during all the phases of the study, both the secondary research and the exploratory analytical phase. There are fewer concerns about privacy and confidentiality in the dataset used for the exploratory analysis, due to the absence of primary identifiable personal information and human-participant records. However, the issue of academic integrity was upheld in that information from secondary sources was presented in an accurate manner, appropriate referencing was used in the IEEE style and analytical methods used on the data presented were reported transparently. There was no attempt to fabricate, select or manipulate data to meet pre-established criteria or conclusions. Special attention should also be paid to the interpretation of findings related to AI as predictive technologies can be used to facilitate decisions relating to critical energy infrastructure. The results from the exploratory analysis are not considered evidence for an autonomous AI system to directly manage a real-world power grid, but rather as research evidence and as information supporting decisions. This will help with responsible interpretation of the proposed framework and not overstate its practical capacities.

3. Results

Temporal Patterns of Renewable Energy Generation

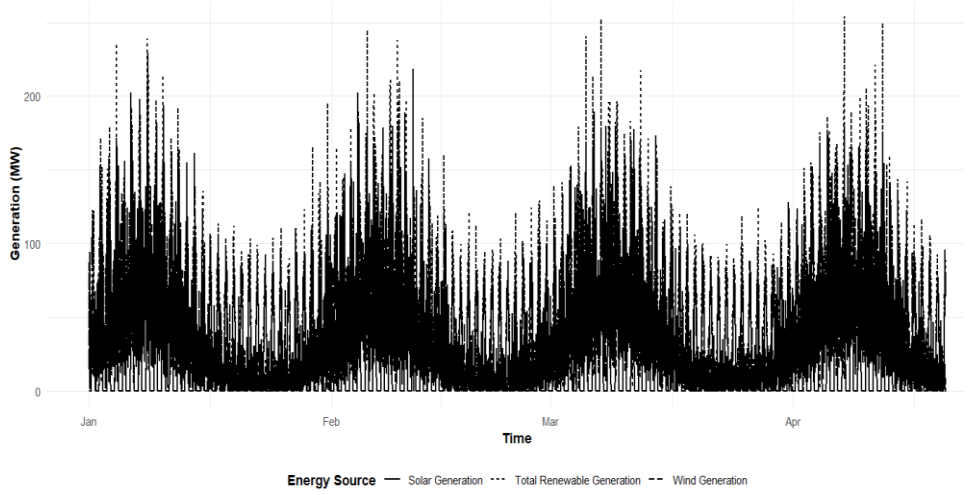


Figure 1. Solar, Wind and Total Renewable Generation Across Observed Energy System (Source: Created by learner)

The chart shows periodic peaks and valleys in solar and wind energy production between January and April, with solar production higher during daylight hours and wind production higher at night. The renewal generation corresponds to these fluctuations, and shows a high temporal dependency on environmental conditions. The frequency of the high generation periods indicates reliable renewable sources throughout some time periods, whereas the low generation periods

indicate variability and require adaptive forecasting for effective real-time integration to ensure grid stability.

Relationship Between Renewable Generation and Environmental Conditions

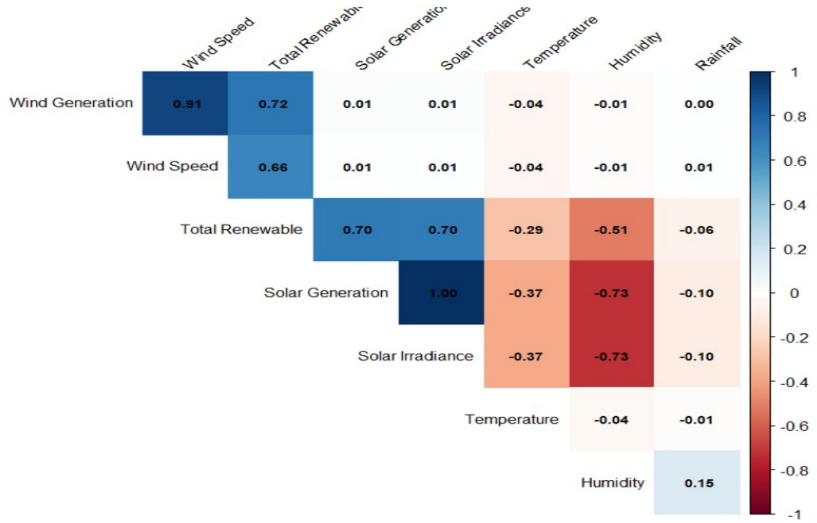


Figure 2. Correlation Between Renewable Generation and Environmental Conditions
(Source: Created by learner)

The correlation heat map indicates that wind generation has a strong correlation with wind speed (0.91), and solar generation is perfectly correlated with solar irradiance (1.00). Humidity and temperature have negative correlations with solar output, which shows that solar output is lower under humid conditions or warmer temperatures. The wind and solar performance is the key factor in total renewable generation, highlighting the importance of incorporating environmental data into predictive models to enhance accuracy and the reliability of renewable forecasting systems.

Renewable Energy Integration and Power-System Balance

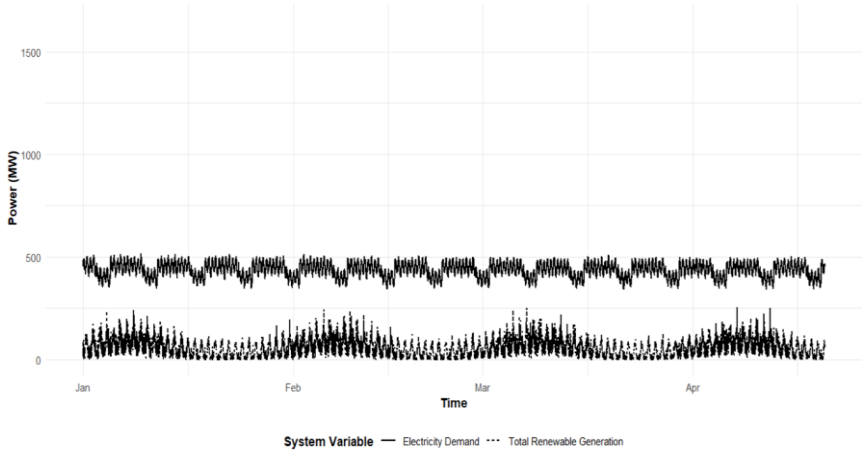


Figure 3. Temporal Comparison of Renewable Supply and Electricity Demand
(Source: Created by learner)

Comparing renewable generation to electricity demand shows an overall supply-demand mismatch, with the amount of renewable energy available falling well short of total demand. The demand is around 400–500 MW, and the renewable power generation is seldom more than 200 MW. This imbalance highlights the need for the intelligent coordination of generation, storage and demand response mechanisms. Successful integration pathways need to guarantee grid reliability and avoid energy curtailment during periods of low electricity generation, when renewable energies are variable.

Battery Storage and Grid Operating Conditions

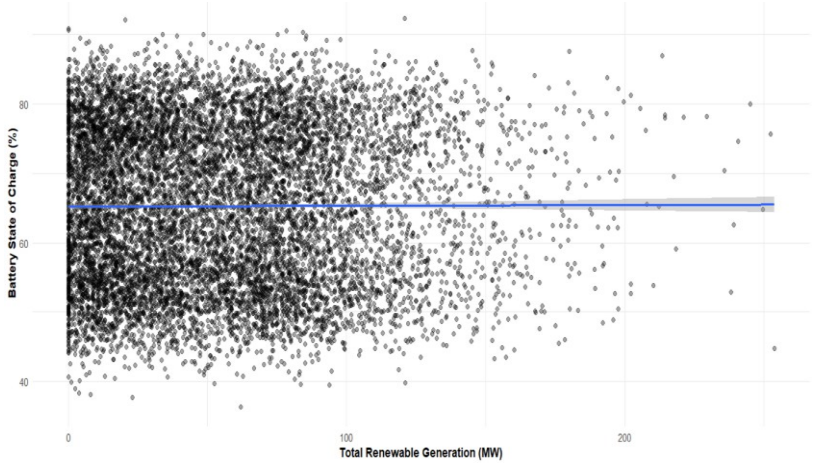


Figure 4. Relationship Between Total Renewable Generation and Average Battery State of Charge (Source: Created by learner)

The scatter plot shows that the battery SoC has relatively constant values with an average of 65-70 % for any renewable generation level. This indicates that storage systems are running within a desirable range and providing grid support when the renewable production is not constant. The minimal correlation between generation and charge level suggests that BMS focuses more on balancing out the stability of the grid rather than direct source of renewables, underscoring the need for optimized control algorithms to ensure energy availability and operational resilience.

4. Discussion

The results demonstrate the dynamic and interdependent nature of renewable generation, environmental conditions, storage, and grid operation. The temporal variation in solar and wind output supports the established view that renewable integration requires adaptive forecasting and real-time coordination [16], [17]. The strong relationship between wind generation and wind speed and the direct relationship between solar generation and irradiance also reinforce the value of incorporating physical relationships into predictive models, consistent with physics-informed approaches described in previous power and energy studies [7], [9].

The persistent gap between renewable generation and electricity demand indicates that forecasting cannot be treated as an isolated prediction task. Grid operation must coordinate generation, demand response, and storage so that forecast information can support system-level decisions. This interpretation is consistent with AI-based demand-side management and scheduling research [5] and with optimization approaches for smart grids and virtual power plants [18]. The relatively stable battery state of charge across varying renewable output further indicates the operational role of storage in smoothing short-term variability and supporting resilience.

The findings also support the proposed integration of physics-informed AI and digital twin technology. A digital twin can provide a continually updated virtual representation of grid conditions, while physics-informed models can constrain data-driven prediction using system relationships. This combination addresses complementary limitations identified in the literature: purely data-driven AI can be sensitive to changing conditions and uncertainty [6], while digital twins depend on accurate data, synchronization, interoperability, and reliable physical-digital correspondence [12], [13], [14]. The proposed framework therefore offers a basis for predictive and responsive renewable-energy management in which forecasting, physical consistency, storage behavior, and grid state are considered together.

Study Limitations and Future Work

There are a few methodological constraints that should be taken into consideration when interpreting the results of this study. The chosen dataset is for a single region (R1), but comprises 12

nodes – this does not reflect the geographical diversity and operational complexity of a national or multi-regional electricity network. It also covers limited periods of longer term seasonal changes in renewable energy generation and electricity demand for the time period of January to April 2026. Moreover, the structured structure of the dataset might not completely capture the uncertainties and measurement challenges and irregular operating conditions of real-world power-grid environments. The exploratory analysis can be used to uncover statistical relationships and patterns but not causal relationships between variables. Furthermore, the work does not include the deployment of a physical DT in an operational electricity network and the validation of a production-ready physics-informed AI system. The result is that the proposed framework is a research-based framework that is backed by an exploratory framework, not a fully validated real-time grid-control system.

Future work should involve creating a fully functional prototype of the physics-informed AI-based digital twin that can simulate and predict the physics of the system in real-time. Including multi-regional and seasonal variations of the data will help to generalize the model and cross validate forecasting accuracy across different conditions. Finally, incorporating uncertainty quantification with reinforcement learning could further improve adaptive decision making in grid operations. Furthermore, future research should investigate how digital twins are able to be interoperable between interrelated infrastructures like transport or storage systems. Adding reliability tests such as cyber security, communication latency, and data integrity, will help to ensure reliability in real-time applications. By working together between academia, industry and policymakers, deployment of smart grid systems can be accelerated to optimize operation of the grid while maintaining its sustainability and efficiency despite the variability of renewables.

5. Conclusion

The study aimed to develop a physics-informed AI-driven digital twin framework for renewable-energy forecasting and real-time power-grid integration. The exploratory findings show that renewable generation is strongly dependent on temporal and environmental conditions, that renewable supply remains substantially below total electricity demand in the analyzed system, and that battery storage provides an important stabilizing function under variable generation. These findings support combining physical principles with AI-based analytics and dynamic digital-twin representation to improve predictive reliability and grid situational awareness. For practical development, hybrid modeling should be coupled with continuously updated environmental, generation, storage, and grid data, supported by intelligent storage control and collaboration among grid operators, renewable-energy developers, researchers, and policymakers. The proposed framework is therefore a research-based foundation for more adaptive, resilient, and sustainable renewable-energy integration rather than a fully validated autonomous grid-control system.

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