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Digital twin-based performance evaluation of a photovoltaic system: A real-time monitoring and optimization framework

Mustafa Fadel[1,2], Fajer M. Alelaj[2,3]
[1]Electrical Engineering Department, Mustansiriyah University, Baghdad, Iraq
[2]School of Engineering, Newcastle University, Newcastle upon Tyne, United Kingdom
[3]Kuwait Institute for Scientific Research, Kuwait City, Kuwait

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ABSTRACT

The digital twin (DT) technology implementation in photovoltaic (PV) systems provides an innovative approach to real-time performance monitoring and predictive maintenance. In this paper, an end-to-end DT framework for real-time performance analysis, fault detection, and optimization of a 250 W PV system is proposed. A physics-based equation and AI-based prediction hybrid DT model is developed through MATLAB/Simulink, trained from real data acquired by means of a testbed. The DT simulates the dynamic physical PV system behavior and adjusts itself using self-correcting algorithms to enhance precision in prediction and forecast power output at high fidelity. Results indicate that the DT gives the true response of the PV system with very small differences attributable to model approximations and sensor faults, 95% error minimization after compensation, and a root mean square error (RMSE) of 2.8 W, indicating its applicability for real-time monitoring and predictive main-maintenance. The work here focuses on the feasibility of applying DTs towards the autonomous optimization of distributed renewable energy systems.

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Corresponding Author:

Mustafa Fadel
Electrical Engineering Department, Mustansiriyah University
Baghdad, Iraq
Email: mustafa_1988abbas@uomustansiriyah.edu.iq

1. INTRODUCTION

Renewable energy systems based on photovoltaic (PV) energy have become a crucial part of sustainable energy portfolios worldwide, with increasing adoption driven by their sustainability and declining cost. However, large PV systems are subjected to many challenges that affect their performance and efficiency, due to their outdoor installations [1], [2]. Challenges such as technical system issues and environmental conditions act as obstacles affecting the system's reliability and life span. The technical challenges include voltage and current fluctuations, high DC voltage ripple, conversion efficiency, power quality issues, thermal management, and degradation over time [3], [4]. Environmental challenges, including dust, snow coverage, and weather variability, also play important roles by impacting the PV system performance [5], [6]. To maintain high operational efficiency under different environmental and technical conditions, sophisticated monitoring and optimization techniques are required. Digital twin (DT) technology emerges as game-changing, by providing a virtual match to the real-world system in real-time. This mirror model of the physical system can offer unprecedented potential in autonomous optimisation and predictive analytics [7]. DT facilitates ongoing evaluation of PV system performance by fusing sensor-driven data collection and computational modelling, enabling proactive fault diagnosis and improved predictive maintenance techniques. The recent state of the art highlights the importance of emerging DT in renewable energy systems, where researchers in [8] found that the DT system could detect different faults, such as 20% drift in sensor reading in the PV conversion unit, within a short duration. Delussu *et al.* [9] compare two different DT approaches to predict solar energy production and create a hybrid DT system by combining the two studied systems to improve predictions. Lee *et al.* [10] propose a novel generative data-driven model based on numerical weather prediction that effectively produces environmental data to simulate the future behaviour of PV DT systems. Moreover, the study in [11] introduces an innovative DT system that integrates a novel circuit-long short-term memory (LSTM) model with a proposed triangle-shading pattern estimation method, eliminating dependencies on direct irradiance sensing and historical data.

2. DIGITAL TWIN TECHNOLOGY

To understand how a DT functions, two key aspects must be addressed. This section will outline the DT design requirements, including the necessary tools for building an efficient virtual system. Furthermore, it explores the development stages of the DT, focusing on its intended function and operational capabilities.

2.1. Digital twin design requirements

To develop an effective DT, there are several technical, data, software, and engineering requirements that must be met to ensure simulation accuracy and optimize performance. Figure 1 illustrates the DT design system, where each PV DT needs hardware infrastructures represented as different types of sensors such as environmental sensors represented by Pyranometers that are used to measure the amount of falling irradiance on PV modules, temperature sensors for PV panels and ambient, humidity, wind speed, and dust sensors to assess the impact of the environment on performance, or electrical measurements sensors such as voltage, current, and power measurements from PV modules and inverters [12], [13]. In addition, each DT requires an edge computing unit that is used to process the initial data before sending it to the cloud to reduce latency and improve DT responsiveness. To ensure data integrity, a reliable communication network is required, for example, different IoT protocols such as Message Queuing Telemetry Transport (MQTT), Open Platform Communications Unified Architecture (OPC UA), or Modbus is required, especially for applications needing fast response and in remote locations [4], [5].

Moreover, the quality of received data and its accuracy play a crucial role in DT performance, where data must be up-to-date, accurate, and uninterrupted to ensure the reliability of the numerical simulation. Additionally, using cloud databases can be efficient for big data processing gathered from real-time analysis and using machine learning (ML) techniques to analyze big data, predict failures, and improve performance. The presence of software support is essential in building a rugged DT system [14], [15]. Data management and artificial intelligence (AI) platforms can predict energy consumption, detect faults, and create interactive dashboards to display data and analyze performance. Furthermore, software programs like MATLAB/Simulink© and NSYS© that use modelling and simulation engines can play an important role in developing accurate physical numerical models based on PV performance equations and the effect of heat on solar panels. Engineering and physical requirements are important to design integrated models for PV systems, where the DT must be able to simulate all PV system components. Components such as solar panels and the effect of gradual corrosion, inverters' effect on performance, batteries (storage systems) and their life cycle based on charging and discharging patterns, and integration with the electrical grid and energy flow management [16]. Moreover, the DT must be designed to be expandable to include large solar power plants or integrated smart electrical grids, and the design must be compatible with the existing solar infrastructure to facilitate integration without the need to redesign the system from scratch [17].

2.2. Digital twin development stages

Digital twin creation is a highly advanced process that moves in different steps to develop an accurate digital model of the physical system's real life. As indicated in Figure 2, the process of DT development can be divided into a series of stages. Data collection and system integration phase, where the DT is based primarily on real data coming from the solar system provided by different types of sensors deployed, and ensuring that data coming from different devices and sources is synchronized. Furthermore, providing communication infrastructure to ensure that the network can transmit data in real time without significant delay and store the gathered data in an appropriate storage mechanism [5]. Model development and simulation is the next phase of DT development, where in this stage the DT will be built depending on type selection whether it is a physics-based twin that relies on physical equations to model the behavior of the system, data-driven twin that relies on AI and data analysis, or hybrid twin that combines physical modeling and AI to increase accuracy [16]. At this stage, model validation and calibration are examined by comparing DT results with real data to detect discrepancies and correct errors, and tune the model based on actual operating data to improve accuracy and reliability.

The next stage is system integration and control, where the digital twin is linked to the actual systems, and intelligent control mechanisms are activated. Integration with systems to monitor the performance of the PV system and to show information and analysis. Additionally, with the use of predictive analytics for fault detection in advance by developing deep learning systems and analyzing patterns for improved energy efficiency, and enabling automatic control and performance optimization through dynamic adjustment of solar inverter parameters based on actual operating conditions [14]. The stage of software development is the final and continuous observation, wherein DT must be executed and observed so that the goals to be realized are achieved by executing and testing the system in real life to see how the digital twin behaves for different operating conditions to confirm its stability, and comparing the predicted results with real data from the real system. Furthermore, continuously updating digital models as new operating data becomes available and tuning software and algorithms to improve performance based on changes in operating conditions by relying on the DT to predict potential failures and take proactive measures, and run real-time analytics to detect any decline in system efficiency [18].

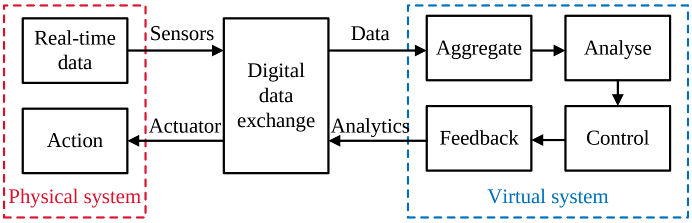

Figure 1. Digital twin system architecture

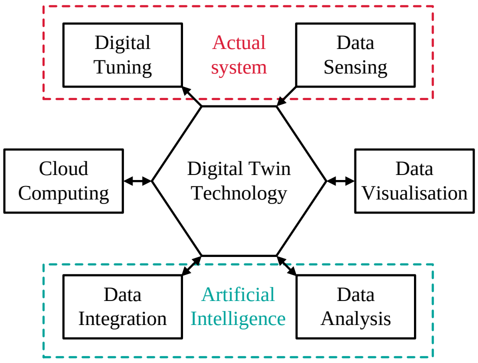

Figure 2. Digital twin development stages

3. DIGITAL TWIN APPLICATIONS IN PV SYSTEM

The modern PV systems utilise the DT to predict and optimise their performance. Providing real-time monitoring to the full PV system can maximise its performance under different environmental conditions. Real-time data are gathered from the PV system to be analysed by the virtual twin, resulting in early prediction of future system issues [6]. Moreover, by using AI tools, the DT can predict possible faults in the PV system, whether at the PV side level, such as PV modules efficiency dropping due to environmental condition fluctuations, or converter level, where components fail (inductor, capacitor, or switches). Spotting these issues can increase the system's reliability by reducing system fault periods and enabling predictive maintenance [19], [20]. Furthermore, increasing the PV system efficiency can be achieved by integrating such technology and experimenting with different scenarios, such as PV module implementation angles to optimise irradiance exposure, the shadowing effect, and different environmental conditions, providing the best settings to increase system efficiency [21]. Also, the DT can be used in smart grids to distribute the power efficiently by storing it or redirecting it to the main grid when needed. Moreover, incorporating DT can help to modify the system design, such as adding new units or changing storage technologies before implementing the physical system, impacting the cost and time [22].

4. CHALLENGES OF DT IN PV SYSTEM

In spite of many benefits being linked with combining DT technology with PV systems, there are several issues related to the use of such technologies. Use of DT entails several technical issues, including the creation of a precise virtual model for the PV system that requires proper understanding of different behaviour of the components of the PV system, such as PV modules, inverters, batteries, and environmental conditions. Modelling such a system requires advanced calculations, including the dynamic changes in irradiance, ambient temperature, and normal ageing in PV modules [14]. In addition, different designs and PV system performance can vary from one location to another making it challenging to develop a general model that suits all applications. Furthermore, DT relies on data acquired from sensor equipment, energy transducers, weather databases, and IoT analytics, with non-unified standardisation for various system equipment makes it difficult to integrate information from different makers [23]. Response time and real-time analysis are others tough ones, in which the DT must assess data and handle errors in real time, that can be backed by powerful cloud computing servers and rapid connectivity networks [16]. Latency in data transmission may affect the speed of decision-making in critical situations, such as sudden failures or low energy efficiency. In addition, DT accuracy can be affected by fluctuations in weather factors, where DT depends on the availability of accurate climate data, and some areas lack of accurate data or are affected by unexpected climate changes, such as dust storms or sudden irradiance changes that may affect the accuracy of DT forecasts [5]. Furthermore, operating in harsh environments requires regular maintenance and continuous replacement, leading to increase operating and maintenance costs.

5. PROPOSED DT SYSTEM

To understand the DT work and test it in a real environment, it is essential to examine it in real-world circumstances with actual data. The full PV system is illustrated in Figure 3(a), which consists of multiple PV units, each connected to the main DC-bus through DC boost converter and connected to a central inverter for microgrid application. The examination will take place through building a virtual twin that simulates the performance of the physical system via sensing and analysing real-world data, where a data acquisition unit logging measurements at 1-minute intervals through sensor network for capturing irradiance, temperature, voltage, and current. The model uses a trained feedforward neural network (FNN) developed using MATLAB's Neural Network Toolbox with 10,080 training samples (1-week, 1-minute resolution). It is a two-hidden-layer, 10 then 15 neuron model, and uses Levenberg-Marquardt (trainlm) training algorithm. There is a module for detecting errors, which measures the difference between the prediction and actual power. When the difference exceeds 5W, a rolling average for 5 intervals is computed and is used to bias the prediction result adaptively. Resulting in a mirrored system uses a feedback loop for error detection and correction, used to optimise the overall system performance and minimise future maintenance. Figure 3(b) shows the circuit diagram of the DC/DC boost converter powered by a PV module with its specifications illustrated in Table 1. Building the DT will be based on modelling the basic physical behaviour of the PV system using mathematical equations for the PV cell [**?**]. For a single-diode PV module, the current-voltage relationship for a PV module is given by (1).

$$I_{pv} = I_{ph} - I_d \left(\exp\left(\frac{V + I_{pv} R_s}{n V_t} \right) - 1 \right) - \frac{V + I_{pv} R_s}{R_{sh}} \tag{1}$$

Where I_{pv} is the PV output current, V_{pv} is output voltage, I_{ph} is the photocurrent, I_0 is the diode reverse saturation current, R_s is the series resistance, R_{sh} is the shunt resistance, n diode ideality factor, and V_t is the thermal voltage given by $V_t = \frac{kT}{q}$. Where k is Boltzmann constant (1.380649×10^{-23} J/K), T is the PV cell temperature, and q is the electron charge ($1.602176634 \times 10^{-19}$ C).

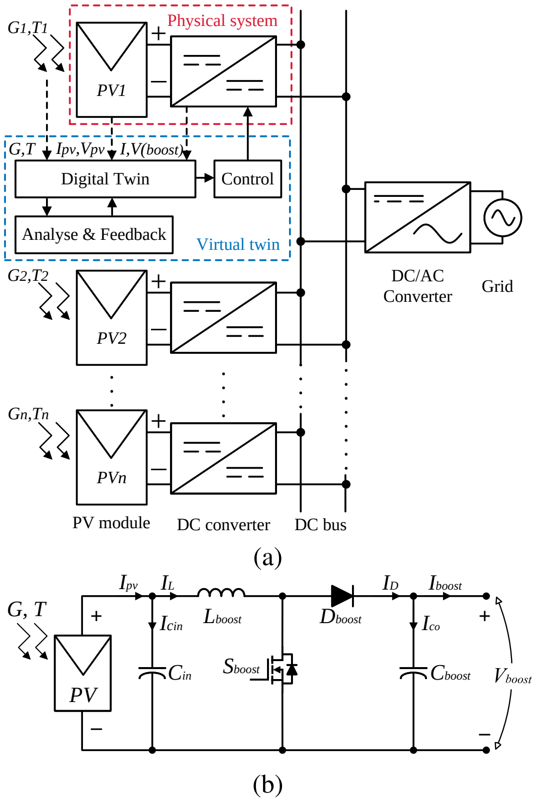

Figure 3. The overall DT proposed system: (a) PV power system and (b) power conversion unit

Table 1. PV panel parameters

Parameter	Symbol	Value	Unit
Rated power	P_{pv_rated}	250	W
Voltage at max power	V_{mp}	30	V
Current at max power	I_{mp}	8.33	A
Open-circuit voltage	V_{oc}	37	V
Short-circuit current	I_{sc}	8.75	A
Number of cells	N_{cells}	60	-
Temperature coefficient of power	β	-0.45	%/°C
Temperature coefficient of voltage	K_V	-0.34	V/°C
Temperature coefficient of current	K_I	0.05	A/°C

The photocurrent (I_{ph}) released by the PV cell is a function of the solar irradiance (G) and temperature (T) given as (2) [8].

$$I_{ph} = (I_{ph,STC} + K_I(T - T_{STC}))\frac{G}{G_{STC}} \tag{2}$$

Where the standard test conditions (STC) are at $T = 25$ °C and $G = 1000$ W/m^2. The diode reverse saturation current is represented as (3) [12].

$$I_0 = I_{0,STC}\left(\frac{T}{T_{STC}}\right)^3 \exp\left(\frac{E_g}{nk}\left(\frac{1}{T_{STC}} - \frac{1}{T}\right)\right) \tag{3}$$

Both open-circuit voltage (V_{oc}) and short-circuit current (I_{sc}) are shown as (4) [25].

$$V_{oc}(T) = V_{oc,STC} + K_V(T - T_{STC}) \tag{4}$$

$$I_{sc}(T) = I_{sc,STC} + K_I(T - T_{STC}) \tag{5}$$

Where K_I and K_V are the temperature coefficients of current ($A/°$C) and voltage ($V/°$C) respectively. The maximum PV power is illustrated as (6).

$$P_{max}(T) = P_{max,STC}\,(1 + \beta(T - T_{STC})) \tag{6}$$

Where β is the temperature coefficient of power.

6. SIMULATION RESULTS AND DISCUSSION

The proposed system will have a 250 W PV module, where a parallel MATLAB/Simulink© model will simulate the expected PV output using single-diode mathematical equations and utilise ML for power forecasting. Using irradiance (pyranometer) and temperature (PT100) sensors to take real-time measurements will help to compute PV panel performance under different environmental conditions. The operation of the DT was validated using real and synthetic data under incremental irradiance (200 to 1000 W/m^2) and temperature (15 °C to 35 °C) variations. The proposed system uses advanced visualisation by providing comprehensive performance plots for system behaviour to varying environmental factors. Figure 4(a) illustrates both real and digital output power response to step-wise irradiance increase, while Figure 4(b), represents the performance under ambient temperature increase, where the output power is affected negatively at higher temperature. Furthermore, Figure 4(c), reveals the effects on PV performance under varying sunlight and temperature conditions. From the illustrated results, it is noticeable that the DT correlated well with the measurements, presenting a small error factor. The AI-enriched DT exhibited high accuracy and low lag in transitions.

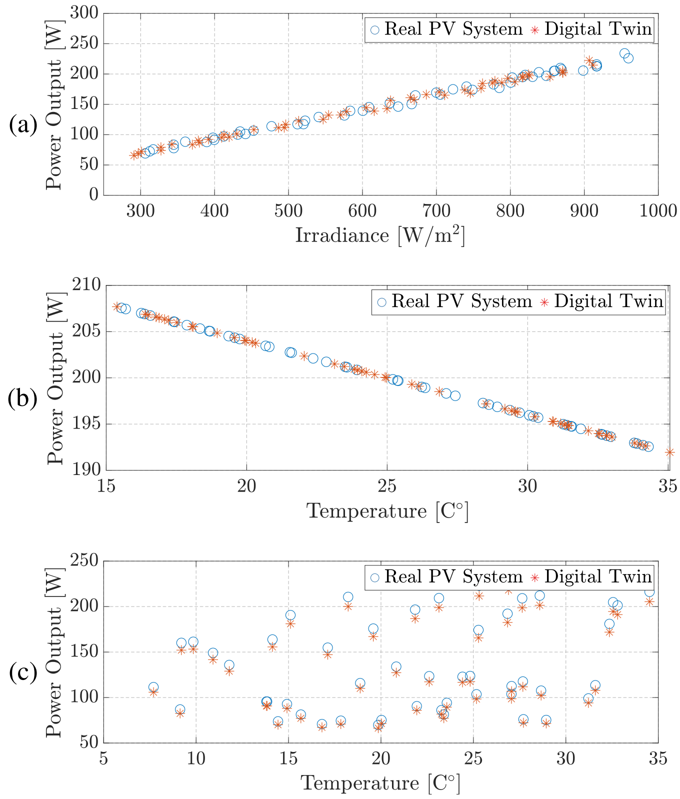

Figure 4. PV output power behaviour under: (a) increasing irradiance, (b) temperature increase, and (c) varying irradiance and temperature.

To test the reliability of DT and how it can adapt to sensor errors and environmental changes without manual intervention, a self-degradation and correction analysis takes place by continuously comparing the predicted power output with the actual measured output. The DT detects periods when predictions deviate significantly from the real system beyond a set threshold value of 5 W (∼2%) of the maximum PV power (250 W), and this deviation persists for three consecutive samples, it flags an anomaly. To correct this, the system employs a five-frame rolling average of past prediction errors and adjusts subsequent predictions by an adaptive bias. This light-weight correction scheme greatly improves real-time alignment without computational overhead. As shown in Figure 5, 39 errors were correctly detected, with no false positives. Observing the system's adaptability to these errors.

The quantitative numerical performance of the DT model was evaluated quantitatively against three common measures of error: root mean square error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2). The DT achieved an RMSE of 2.8 W, which indicates that, on average, the simulated power output deviated from the measurement by 2.8 watts, with greater sensitivity to larger errors. The MAE was 2.1 W, representing a low and relatively stable mean absolute prediction error over the dataset. The model also had an R^2 of 0.984, which confirms that 98.4% of the variance in actual PV power output was well represented by the predictions from the DT. These results confirm the high accuracy and reliability of the DT model in the simulation of the real-time operating behaviours of the photovoltaic system under various environmental conditions. Figure 6 displays how self-correction mechanisms adjust these deviations as the DT corrections align closely with real system performance, with error reduction after correction reaching 95%. To ensure rugged performance under varying conditions, power loss trends over time are highlighted in Figure 7, where it represents how much power the DT model underestimates compared to the physical system over time, and the maximum power error found is 11.2 W. This is crucial as identifying where and when the losses occur can be efficient for refining the DT's prediction model, resulting in optimizing the overall performance. Figure 8 compares the dynamic efficiency of the physical PV system and digital twin in a period of 50 seconds. The two curves are virtually identical with a difference of less than 0.1%, confirming the reliability of the DT to reproduce the dynamic performance of the system. The agreement proves the reliability of the DT to track efficiency and its applicability for diagnostics and optimization. Figure 9 illustrates a histogram of power prediction errors between the actual PV system and digital twin, from 4 W to 11 W. Most errors are concentrated in the ranges 5–6 W and 10–11 W, indicating that while DT is generally accurate, larger deviations could occur during dynamic transitions or sensor faults. These variations are within the real-time prediction tolerance, and the spread warrants the use of DT's self-correction facility to adaptively reduce such discrepancies.

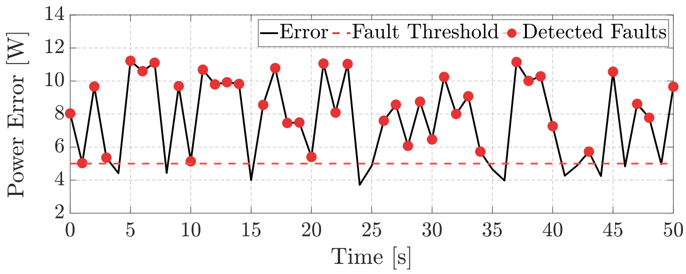

Figure 5. Virtual twin fault detection and deviation

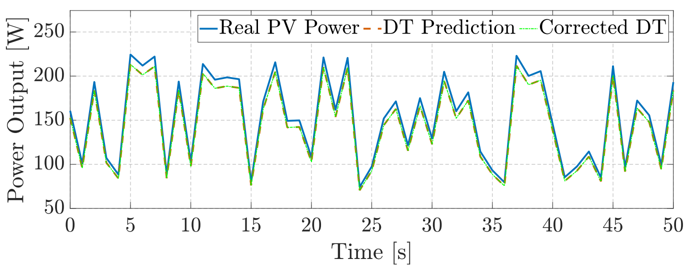

Figure 6. Power output with digital twin correction

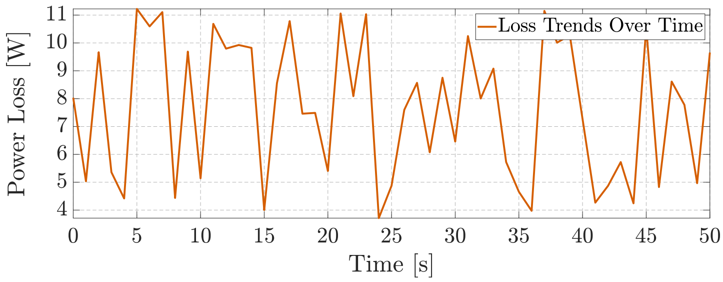

Figure 7. Mirrored system power loss over

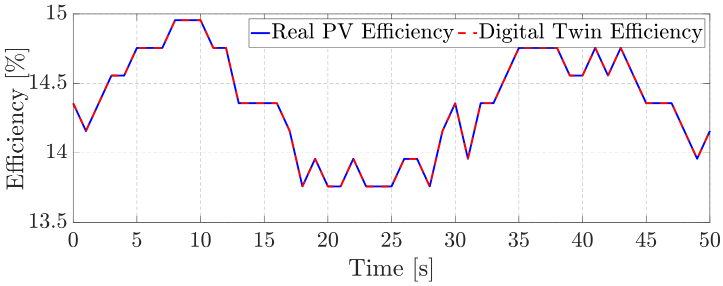

Figure 8. Histogram of digital twin power prediction

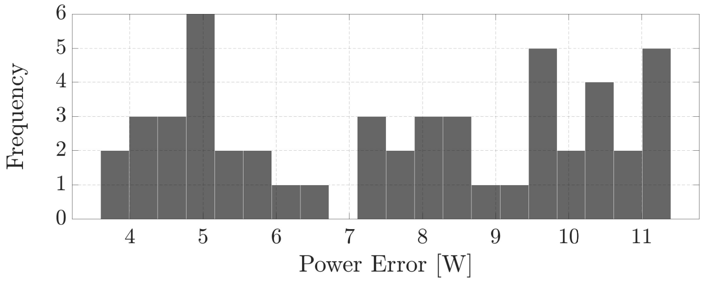

Figure 9. Histogram of digital twin power prediction errors

7. CONCLUSION

The implementation of DT technology on renewable energy systems is a tremendous advancement in real-time monitoring, fault diagnosis, performance improvement, and predictive maintenance. A hybrid DT model of a 250 W PV system was proposed in this study by the fusion of physics-based equations and AI-based prediction. The system was very accurate in replicating real-world PV behaviour, with an RMSE of 2.8 W and a coefficient of determination (R^2) of 0.984. Reliability was also enhanced by an inherent self-correcting mechanism, with reductions in error deviations of up to 95% across 39 anomalies that were detected. Power loss analysis showed the 11.2 W peak prediction error in the dynamic environment conditions, revealing the DT's variability diagnosis and compensation capability in practical operation. System experimental verification was conducted using real-time data, illustrating pragmatic usefulness. These findings depict the potential of DTs in facilitating smart, autonomous energy systems that react dynamically and pave the way for integration with storage, smart grids, and edge computing platforms.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Mustafa Fadel	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Fajer M. Alelaj		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
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

Derived data supporting the findings of this study are available from the corresponding author, [MF], on request.

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BIOGRAPHIES OF AUTHORS

Mustafa Fadel received his B.Sc. degree in Electrical Engineering from Mustansiriyah University, Baghdad, Iraq, in 2010, and his M.Sc. degree in Electrical Engineering from the same university in 2016. He is currently pursuing a Ph.D. at Newcastle University, United Kingdom. From November 2016 to May 2019, he served as an Assistant Lecturer in the Electrical Engineering Department at Mustansiriyah University, where he was later promoted to Lecturer in October 2019. His research interests focus on the design and control of power electronic converters for renewable energy systems, electric vehicles, battery charging systems, and wireless power transfer applications. Mustafa was the recipient of the First Prize Paper Award at the IEEE International Symposium on Electrical, Electronics, and Information Engineering, Leicester, United Kingdom, in 2024. He can be contacted at email: mustafa_1988abbas@uomustansiriyah.edu.iq.

Fajer M. Alelaj was awarded a Bachelor's degree in Electrical Engineering from Kuwait University in 2014, earning a place on the honor list twice. She obtained her MSc in Electrical Power from Newcastle University, United Kingdom, in 2020, graduating with First Class Honours. She has recently completed her Ph.D. in Hybrid Distribution Transformers at Newcastle University. She was also the recipient of the M.Sc. Prize for the top-ranked postgraduate taught student in Electrical & Electronic Engineering for the academic year 2019/2020. She can be contacted at email: felaj@kisr.edu.kw.