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A Digital-Twin-Based Intelligent Operation and Maintenance System for Photovoltaic Power Stations

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Abstract

Operation and maintenance of photovoltaic (PV) power stations is conventionally reactive: faults are found by periodic manual inspection, so the interval between a performance loss and its diagnosis can be long, and the energy lost during that interval is unrecoverable. This paper presents a low-cost intelligent operation-and-maintenance (O&M) system in which a digital twin — a cloud-resident virtual counterpart of the physical installation — is continuously updated from field sensors and used to interpret plant behaviour. The bench-scale implementation combines a solar panel with a rectifier diode, a 3.7 V battery bank, a 7805 regulator, a voltage sensor, a light-dependent resistor (LDR), a rain-drop sensor and a NodeMCU ESP8266, with remote visualisation through the Blynk IoT platform. Three environmental conditions were instrumented and recorded. Under normal light with no rain the panel delivered 10.44 V; under low light with rain the output collapsed to 0.43 V; and under low light without rain it recovered only to 1.08 V. These three measurements are the complete recorded dataset and are reported as such: they establish that the system correctly distinguishes a productive state from two distinct unproductive states, and that low irradiance rather than precipitation is the dominant factor, since the no-rain low-light case remained more than an order of magnitude below the normal-light case. Because irradiance was not logged in physical units and no measurement was repeated, no efficiency figure, no power curve and no quantified predictive-maintenance accuracy can be derived from this dataset, and none is claimed. The contribution is a demonstrated, fully traceable sensing-to-dashboard path together with an explicit statement of the additional instrumentation required to make the assessment quantitative.

Introduction

Rising demand for renewable generation has driven wide deployment of photovoltaic (PV) power stations. The generating equipment itself is largely static, but the operation and maintenance (O&M) practice surrounding it has not kept pace. Conventional O&M relies on delayed fault detection, manual inspection routines and correspondingly high operating cost; the practical consequence is energy lost between the onset of a fault and its discovery, and a reduction in realised system efficiency that is invisible until an inspection happens to reveal it. This paper proposes an intelligent O&M system built on digital twin technology, combining IoT-based real-time monitoring with cloud-side analysis. A digital twin is a virtual replica of a physical asset that is kept synchronised with it by a stream of measurements, so that the state of the asset can be examined, simulated and interrogated without being physically present at the site.

The proposed system instruments a small PV installation with a rain-drop sensor, a light-dependent resistor (LDR) and a voltage sensor, together with a NodeMCU ESP8266 microcontroller, 3.7 V batteries, a 7805 voltage regulator and a solar panel with a rectifier diode. The Blynk IoT platform provides the remote interface, allowing voltage, environmental condition and system status to be reviewed from any location. The objective is to shorten the interval between a change in plant condition and the operator becoming aware of it.

1. Research Gap

Two bodies of work bracket the problem. Monitoring studies instrument PV plants thoroughly and report the resulting data, but stop at visualisation. Digital-twin and predictive-maintenance studies model plant behaviour in depth, but generally assume a well-instrumented source with irradiance, temperature and electrical quantities all logged in engineering units. There is comparatively little work that carries a genuinely low-cost, sparsely instrumented installation through to a working twin while stating plainly which conclusions that instrumentation can and cannot support.

2. Contributions

1) A complete low-cost sensing-to-dashboard implementation for PV condition monitoring, specified at component level and reproducible from the description given.

2) A transparent report of the three recorded operating conditions, with the measured terminal voltage for each and the system's corresponding classification.

3) An explicit account of what the recorded dataset cannot support — efficiency, power curve, and predictive-maintenance accuracy — together with the reason in each case.

4) A statement of the additional measurements required to make the assessment fully quantitative, and of the three failure modes observed during operation.

Section II reviews related monitoring work. Section III describes the system architecture. Section IV details the materials and methodology. Section V reports the recorded results and Section VI discusses them. Section VII states the limitations, Sections VIII and IX give the applications and conclusion, and Section X the future scope.

Related Work

Table I summarises the monitoring and control studies reviewed during this work, as recorded in the project literature survey. Taken together they establish two things: that microcontroller-and-cloud architectures are now the standard approach to PV monitoring, and that the reported systems concentrate on acquisition and display rather than on interpretation of the acquired data.

Table 1. Reviewed Work on Solar Plant Monitoring and Control

Author (year)	Approach and findings
Dipen Dutta et al. (2016)	IoT monitoring of PV mini-grids using publisher–subscriber communication with ESP32 and a cloud platform acting as MQTT broker. Reported small measurement error and real-time broker response.
Haider-e-Karar et al. (2014)	LabVIEW server and client graphical interfaces for local and remote control of DC power from solar panels, with Arduino Uno, current and voltage sensors, relays and a charge controller; records history for later analysis.
Ali Hosein Arianfar et al. (2012)	Internet-based monitoring of a linear parabolic solar plant; identifies variable network delay as the principal obstacle and adopts the wave-variable method to accommodate it.
Chiung-Hsing Chen et al. (2014)	LabVIEW-based wind and solar storage monitoring with wireless transmission to a database, aimed at improving the accuracy of smart-grid data computation.
Nyoman Sugiartha et al. (2013)	Stand-alone PV monitoring prototype using ESP32 DEVKIT V.1 and Blynk, with PZEM-017 DC energy sensors at panel output, battery and load; 120 Wp panel, 20 A MPPT controller, 12 V/100 Ah battery.

Jongwoo Choi et al. (2016)	Web-based monitoring that draws environmental data from a national weather service open API, avoiding the cost of per-plant weather sensors.
Anupama Patil et al. (2018)	Remote data acquisition for solar plants over IoT reporting net power, total energy and irradiance to schedule preventive maintenance.
Zhen-jia Sun et al. (2015)	Solar power system for wireless-sensor-network nodes in forest monitoring, with step-up and step-down conversion to sustain node operation in low light.
Zainah Md. Zain et al. (2016)	Solar-powered real-time water-quality monitoring with wireless transmission to a remote GUI and automated SMS warning above threshold.
Nurzhigit Kuttybay et al. (2014)	Intelligent solar tracking with cloud detection; horizontal auxiliary module compared against a tracking module to select panel orientation. Reports 18 % more energy in cloudy weather than a biaxial tracker alone.

The comparison of Table I motivates the present design in two respects. First, environmental sensing is repeatedly shown to matter — both Choi et al. and Kuttybay et al. demonstrate that knowledge of weather state changes what the operator should do — which supports the inclusion of light and rain sensing alongside electrical measurement. Second, none of the reviewed systems maintains a synchronised virtual counterpart of the plant against which live readings can be compared, which is the function the digital twin performs here.

System Architecture

The system architecture is shown in Fig. 1. A solar panel charges the battery bank through a rectifier diode. The 7805 regulator derives a stable rail for the microcontroller and sensors from the battery. The NodeMCU ESP8266 acquires the rain-drop, LDR and voltage-sensor channels, and transmits the acquired state over Wi-Fi to the cloud, where the digital twin model resides. The Blynk application provides the operator-facing display.

1. Sensing Layer

Three quantities are acquired. The rain-drop sensor reports the presence of precipitation, which affects panel output and may indicate a risk of water ingress. The LDR reports incident light intensity, which determines the power available to be generated. The voltage sensor reports panel and battery terminal voltage, which together indicate whether the energy produced is reaching storage.

2. Processing and Communication Layer

The NodeMCU ESP8266 serves as the central processing unit. It samples the three sensor channels, applies the classification logic and communicates over Wi-Fi to the cloud-hosted twin. Because the classification decision is evaluated on the microcontroller, the local LED indicator and lever switch continue to convey operational state at the installation even when the network is unavailable.

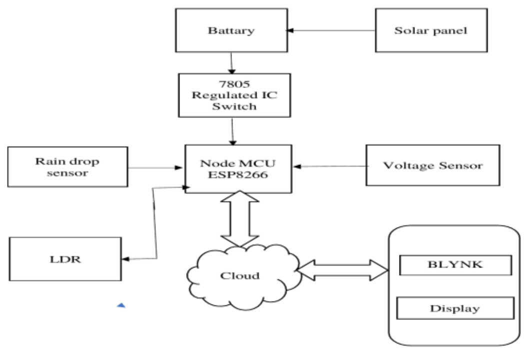

Figure 1: Block diagram of the proposed digital-twin-based PV operation and maintenance system.

3. Digital Twin and Presentation Layer

The cloud-resident twin receives the transmitted state and maintains a running representation of the installation. Live readings are compared against the accumulated operational record so that a departure from the expected pattern — a voltage lower than the prevailing light level would predict, for example — can be surfaced as a maintenance indication rather than merely displayed. The Blynk dashboard presents the current light status, rain status, measured voltage and the resulting system suggestion.

Materials and Methods

1. Components

Table 2 lists the components used in the implementation and the role of each.

Table 2. System Components and Their Function

Component	Function in the system
NodeMCU ESP8266	Central controller; sensor acquisition and Wi-Fi uplink
Solar panel with rectifier diode	Generation; diode prevents reverse discharge into the panel
Voltage sensor	Panel and battery terminal voltage measurement
Light-dependent resistor (LDR)	Incident light intensity sensing
Rain-drop sensor	Precipitation detection
Battery, 3.7 V × 3	Energy storage and controller supply
7805 voltage regulator	Stabilised rail for controller and sensors
LED indicator and lever switch	Local on-site status and manual control
Blynk IoT application	Remote dashboard and alerting

2. Controller

NodeMCU is an open-source IoT platform comprising firmware that runs on the Espressif ESP8266 Wi-Fi system-on-chip and hardware based on the ESP-12 module. The firmware uses the Lua scripting language and derives from the eLua project, built on the Espressif Non-OS SDK. Unlike the bare ESP8266 module, the development board includes a CP2102 USB-to-TTL converter for programming and debugging and is breadboard-compatible. The board and its input/output allocation are shown in Figs. 2 and 3.

Figure 2: NodeMCU ESP8266 development board used as the system controller.

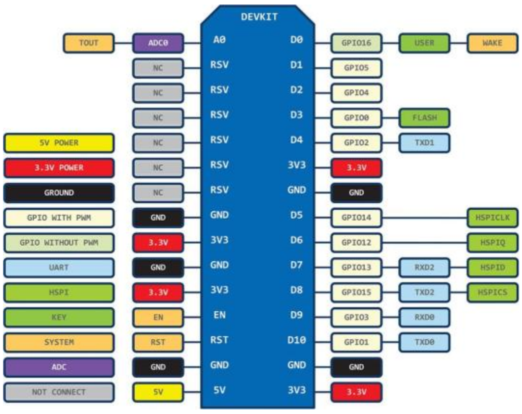

Figure 3: NodeMCU general-purpose input/output allocation.

3. Sensors and Generation

The voltage sensor (Fig. 4) provides the electrical measurement channel and reports the terminal voltage available at the battery. The LDR (Fig. 5) varies its resistance with incident illumination and provides the light-intensity channel. The rain-drop sensor (Fig. 6) detects precipitation on its sensing plate. The solar panel (Fig. 7) is the generating element and is connected through a rectifier diode to the battery bank.

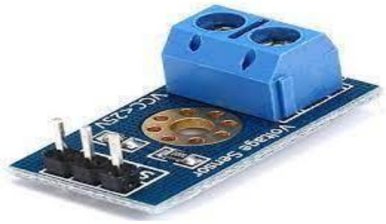

Figure 4: Voltage sensor module.

Figure 5: Light-dependent resistor module for light intensity sensing.

Figure 6: Rain-drop sensor module.

Figure 7: Solar panel used as the generating element.

4. Remote Monitoring Platform

Blynk provides the cloud service and mobile interface (Fig. 8). The NodeMCU associates with the local Wi-Fi network and publishes the acquired state to the Blynk server, which drives the dashboard widgets and the notification path. No local server installation is required.

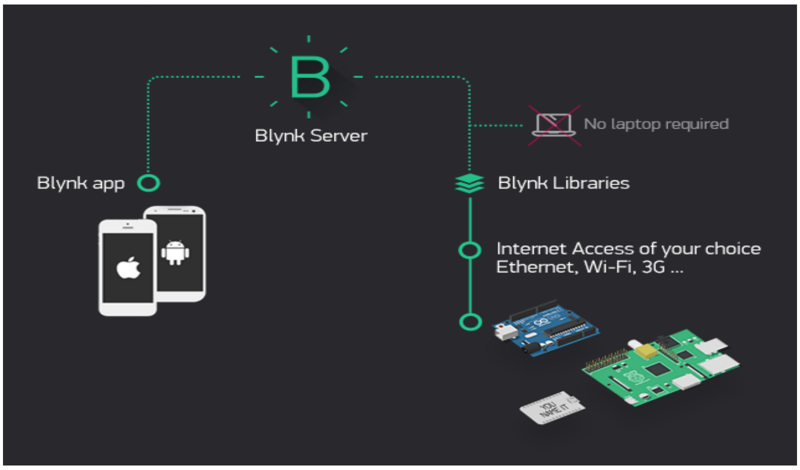

Figure 8: Blynk IoT platform architecture linking the device, cloud server and mobile application.

5. Methodology

The work proceeded in five stages.

Hardware integration

The solar panel, batteries, 7805 regulator, NodeMCU, rain-drop sensor, LDR, voltage sensor, lever switch and LED indicators were assembled into a functional monitoring unit. The panel and rectifier diode charge the batteries to maintain continuous supply, while the regulator stabilises the rail feeding the controller and sensors.

Data acquisition

The sensors acquire environmental and electrical data. The rain-drop sensor detects precipitation affecting panel performance; the LDR measures sunlight intensity to indicate generation potential; and the voltage sensor monitors battery and panel voltage. The NodeMCU processes these channels as the central processing unit.

IoT implementation

The acquired state is transmitted over Wi-Fi to the Blynk platform, enabling real-time monitoring and remote access. The same transmission supplies the cloud-based digital twin model.

Digital twin development

The twin compares live sensor data against the accumulated operational record in order to identify efficiency drops and emerging maintenance needs, so that intervention can precede rather than follow a failure.

Testing and optimisation

The completed system was exercised under differing environmental conditions. Data-transmission behaviour, sensor readings and the classification response were assessed across the test cases described in Section V, and the dashboard configuration and sensor calibration were adjusted accordingly.

Results

The assembled installation is shown in Fig. 9. It comprises the solar panel, NodeMCU ESP8266, the three sensors, the voltage regulator and the battery bank on a single mounting board.

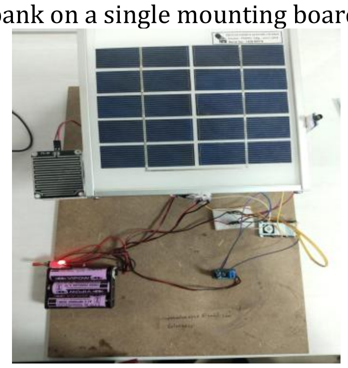

Figure 9: Physical hardware setup comprising the solar panel, NodeMCU ESP8266, sensors, voltage regulator and battery bank.

Three environmental conditions were instrumented and recorded through the Blynk dashboard. The dashboard states for the three cases are reproduced in Figs. 10 to 12, and the recorded values are collected in Table 3.

Figure 10: Dashboard state under normal light with no rain; recorded terminal voltage 10.44 V, classified as suitable for power production.

Figure 11: Dashboard state under low light with rain; recorded terminal voltage 0.43 V.

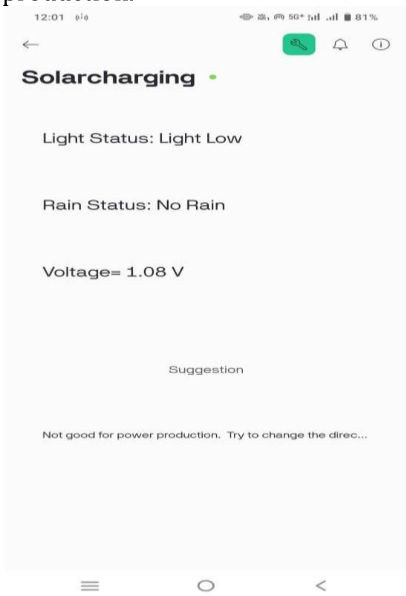

Figure 12: Dashboard state under low light with no rain; recorded terminal voltage 1.08 V.

Table 3. Recorded Operating Conditions and System Response

Condition	Light status	Rain status	Voltage (V)	System suggestion
Good sunlight, no rain	Light normal	No rain	10.44	Good for power production
Low light, raining	Light low	Raining	0.43	Not good — try changing the panel's direction
Low light, no rain	Light low	No rain	1.08	Not good — reposition or wait for improved lighting

1. Reading of the Recorded Data

Two features of the dataset must be stated plainly. First, it consists of three readings, one per condition, with no repetition; the values are therefore single observations rather than means,

and no statement about scatter or repeatability can be made from them.
Second, the three values separate cleanly and in the expected direction. The normal-light case exceeds the two low-light cases by roughly an order of magnitude, which confirms that the voltage channel responds to the quantity it is intended to track. Within the two low-light cases, the no-rain reading (1.08 V) exceeds the raining reading (0.43 V) by a factor of about 2.5, but both remain far below the normal-light value. The useful inference is therefore that low irradiance, not precipitation, dominates the loss: removing the rain while leaving the light low recovers only a small fraction of the normal-light output. This is consistent with the system suggestion returned in each case, which directs the operator to reposition the panel or await better light rather than to address the rain.

2. Monitored Parameters and Local Conditioning
The parameters carried through to the dashboard were solar light intensity from the LDR, environmental moisture from the rain-drop sensor, battery terminal voltage from the voltage sensor, and the resulting status and alert state. The 7805 regulator maintained a consistent supply to the controller and sensors throughout, protecting the electronics from the spikes and dips that accompany a fluctuating solar input; the lever switch and LED indicators provided immediate operational feedback at the installation itself.

Discussion
The result of substance is that the complete path — sensing, local classification, wireless transmission, cloud twin and remote dashboard — was demonstrated end to end on low-cost hardware, and that the three instrumented conditions were distinguished correctly. For an operator, this shortens the interval between a change in plant condition and awareness of it from the inspection period to the transmission period.
The predictive-maintenance function must be described carefully. The twin compares live readings against the accumulated operational record and is intended to forecast battery over-discharge, underperformance from low light or panel misalignment, and environmental disruption to generation. That capability is architectural: it follows from the comparison the twin performs. It was not, however, quantified in these trials. No fault was seeded, no failure was predicted in advance and subsequently confirmed, and no detection rate or false-alarm rate was measured. Claims that the system reduced downtime or extended equipment life would therefore not be supported by the data recorded here, and none is made.
The same caution applies to efficiency. Because irradiance was recorded only as a two-state light classification rather than in W/m^2, and because current was not logged alongside voltage, neither conversion efficiency nor a power curve can be computed from this dataset. The three voltage readings bound the observed operating range and nothing further.

Limitations
Three difficulties were observed during operation, alongside the dataset limitations already noted.

- Wi-Fi dependency. Real-time transfer was occasionally disrupted where internet coverage was poor, interrupting remote visibility. Local indication continued, since classification executes on the controller.
- Sensor accuracy. Dust accumulation on the panel and transient shading distorted light-intensity readings, which in turn affects the energy-management interpretation placed on them.
- Rain sensor sensitivity. False positives occurred from high humidity or condensation in the absence of actual rainfall.
- Dataset sparsity. Three unrepeated readings, with irradiance recorded categorically rather than in physical units and with no current measurement, preclude efficiency, power-curve and predictive-accuracy analysis.

The measurements required to close these gaps are specific: an irradiance sensor reporting W/m^2; a current channel alongside the existing voltage channel, so that generated power can be computed; time-stamped logging over a continuous period rather than isolated readings; and a seeded-fault trial in which a known degradation is introduced and the twin's response recorded against it.

Applications
The architecture is applicable wherever PV generation must be supervised without continuous physical attendance.

- Large-scale solar farms and utility-scale stations, for continuous supervision and maintenance scheduling across dispersed arrays.
- Residential rooftop installations, where the owner receives alerts on voltage drop, shading or environmental change through the mobile application.

- Industrial and commercial installations, where faults may otherwise be detected only through their effect on production.
- Smart-city infrastructure, including solar streetlights, charging points and public buildings managed by a municipal operator.
- Remote and off-grid systems serving rural electrification, where battery level and consumption require tracking and site visits are costly.
- Agricultural applications such as solar irrigation, greenhouses and crop-monitoring installations dependent on stable supply.
- Research and teaching, where the twin provides a live environment for studying PV system behaviour.

Conclusion

A digital-twin-based intelligent operation and maintenance system for photovoltaic power stations has been designed, implemented and tested at bench scale. Using a NodeMCU ESP8266, a voltage sensor, an LDR, a rain-drop sensor and the Blynk platform, the system acquires the environmental and electrical state of a PV installation, classifies it locally and publishes it to a cloud-resident twin for remote review.

Three environmental conditions were recorded: 10.44 V under normal light without rain, 0.43 V under low light with rain, and 1.08 V under low light without rain. The system classified all three correctly and issued the corresponding operator guidance. The separation between the readings identifies low irradiance rather than precipitation as the dominant cause of the observed output loss.

Because the dataset comprises three unrepeated readings, with light recorded categorically and current not logged, no efficiency value, power curve or predictive-maintenance accuracy has been derived from it, and none is reported. Three operational limitations — network dependency, light-sensor distortion from dust and shading, and rain-sensor false positives — were observed and are stated rather than omitted. The contribution of the work is a demonstrated and fully traceable path from low-cost field sensing to a cloud digital twin, together with the specific measurement plan needed to make the assessment quantitative.

Future Scope

1. Instrumentation and validation-The immediate priority is to close the measurement gaps of Section VII: add an irradiance sensor reporting physical units, add a current channel so that generated power can be computed, log continuously with time stamps, and run a seeded-fault trial so that predictive performance can be measured rather than asserted.
2. Machine learning and analytics-With a continuous logged record in place, machine-learning analysis of long-term performance data could estimate panel degradation, battery efficiency and power fluctuation, and optimise energy distribution and storage.
3. Edge computing-Processing sensor data locally rather than relying solely on the cloud would reduce latency and permit continued operation where connectivity is limited.
4. Communication resilience-GSM, LoRa or satellite links would improve transmission in remote and off-grid locations, and would address the network dependency identified above. Integration with smart-grid systems would support coordinated power distribution.
5. Self-cleaning and self-diagnosis-Automated robotic or electrostatic cleaning would address the dust accumulation that distorts the light-intensity channel, and self-diagnosing mechanisms would reduce the need for human intervention.
6. Storage and system expansion-Next-generation storage such as solid-state batteries or supercapacitors would improve energy retention, while extension to hybrid sources including wind and hydro would create a multi-source renewable network managed by a single twin. Blockchain-based energy trading has been proposed as a route to decentralised exchange of surplus generation within a smart-grid ecosystem.

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References

S. S. Kamble and M. I. Waheed, "Solar tracker with improved efficiency using power saving," in Proc. 2nd International Conference for Convergence in Technology (I2CT), 2017, pp. 439–443.

R. Banerjee, “Solar tracking system,” International Journal of Scientific and Research Publications (IJSRP), vol. 5, no. 3, Mar. 2015.

F. Mustafa, Dual-Axis Solar Tracking Over Fixed Solar Systems, 2016, pp. 563–568.

N. D. Watane and R. A. Dafde, “Automatic solar tracker system,” 2013.

M. S. Munna, M. A. I. Bhuyan, K. M. Rahman and M. A. Hoque, “Design, implementation and performance analysis of a dual-axis autonomous solar tracker,” in Proc. 3rd International Conference on Green Energy and Technology (ICGET), 2015, pp. 1–5.

G. Liu, A. O. Baba and L. Zhu, “Hybrid controller for dual-axes solar tracking system,” in Proc. 36th Chinese Control Conference (CCC), 2017, pp. 3203–3207.

D. C. Huynh, T. M. Nguyen, M. W. Dunnigan and M. A. Mueller, “Comparison between open- and closed-loop trackers of a solar photovoltaic system,” in Proc. IEEE Conference, 2013.

D. R, V. Bharathi, R. Ranjitha, A. Ponni, S. Depthi and P. Mageshkannan, Comparison of Efficiencies of Solar Tracker Systems with Static Panel, Single-Axis Tracking System and Dual-Axis Tracking System with Fixed Mount, 2013, pp. 1925–1933.

D. Artanto, A. Prasetyadi, D. Purwadianta and R. Sambada, “Design of a GPS-based solar tracker system for a vertical solar still,” in Proc. International Conference on Smart Green Technology in Electrical and Information Systems (ICSGTEIS), 2016, pp. 140–143.

R. I. Putria, S. Wibowo and M. Rifa, “Maximum power point tracking for photovoltaic using incremental conductance method,” in Proc. 2nd International Conference on Sustainable Energy Engineering and Application (ICSEEA), 2014.

R. Binu Ben Jose, M. E. Shajini Sheeba, K. Ezhil Vignesh, Jarin T., and P. Muthukumar, “Power Quality Enhancement in IOT Based Hybrid Renewable Energy Systems Using D-STATCOM,” in 2023 International Conference on Circuit Power and Computing Technologies (ICCPCT), pp. 1767–1772, 2023.