AI-Driven Maintenance Optimization for Solar Minigrids: A Work In Progress Framework

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***Abstract*—Solar minigrids are a paradigm shift in rural electrification, but their sustainability is constrained by equipment failures, high cost of maintenance, and delayed supply chain services. This paper presents a targeted literature review focusing on key research gaps in AI-driven maintenance optimization applied to solar minigrids and suggesting an integrated framework in addressing these gaps. The gaps are mapped to four research questions: (a) minigrid component's supply chain integration with predictive maintenance outputs, (b) holistic AI frameworks for minigrid predictive maintenance to improve reliability and component life span (c) validation of business models in minimizing maintenance costs, and Return on Investment (ROI) of minigrids (d) integration of inclusivity in equalizing distribution for all community members. The proposed framework integrates IoT sensors, MQTT/LoRaWAN communication, synchronization of the digital twin and AI-based health scoring with supply chain optimization. The framework will be validated using an experimental setup representing a laboratory-scale grid-connected solar photovoltaic power conversion system, and addresses research objectives: predictive maintenance strategy, supply chain optimization, business model design, and inclusive deployment. This study provides a base foundation towards scalable, cost-effective predictive maintenance systems to fill the gap between technical innovation and practical deployment especially in off-grid conditions where resources are constrained.**

Keywords: Predictive Maintenance, Minigrids, Artificial Intelligence, Digital Twin, supply chain integration, rural electrification, Internet of Things

I. INTRODUCTION

Affordable and sustainable energy will continue to be a core requirement of economic growth, especially in rural and off-grid areas. As of 2024, 730 million individuals across the world have no access to electricity, most of them being clustered in Sub-Saharan Africa and South Asia [1]. Solar minigrids have already become an option to serve these underserved population groups, which has allowed applications like household, irrigation, cold storage, and small-scale manufacturing that can generate economic development. However, the operational stability of minigrids depends greatly on optimal maintenance and fault detection. System failures, unexpected downtime, and cost-prohibitive maintenance can stop large-scale adoption and sustainability [2]. Also, failure to properly manage faults in photovoltaic (PV) systems can result in prolonged energy losses, creating massive economic and environmental issues for the end user [2]. The nature of minigrid systems of photovoltaic arrays, battery energy storage, inverters, and distribution networks requires advanced predictive maintenance (PdM) methods beyond the conventional reactive or time-based maintenance models. Also, the ability to predict and schedule maintenance is critical in ensuring long-term operation, especially in developing countries and resource-poor areas.

Recent advances in artificial intelligence (AI) and machine learning (ML) present very promising approaches for addressing this issue. The convergence of AI, Internet of Things (IoT) and the Digital Twin (DT) technologies open an opportunity to turn Minigrid maintenance into predictive, rather than reactive [3], [4]. PdM models also entail prognostics in order to predict system degradation and pre-plan interventions. The integration of AI and IoT devices, DT, and autonomous monitoring systems has allowed acquiring data in real time and the scheduling of maintenance adaptively. These combinations support multimodal data integration, including electrical data, thermal data, meteorological information, and inverter signals, which increase the accuracy of diagnostic results PdM takes advantage of the real-time monitoring system and AI algorithm to predict the failure of the equipment, optimizing the intervention timing, and minimizing lifecycle costs [2]. It is a paradigm shift when resources are scarce, the technical expertise is limited, and the maintenance supply chain is unreliable. This motivates the examination of the existing literature and to identify the gaps in the implementation of AI-based PdM in off-grid solar minigrids.

A. *Objectives of Research*

This paper attempts to address two elements:

- A targeted review to learn the current findings in AI-based PdM for solar minigrids and microgrids and outline key research gaps for our aimed research objectives.
- Proposing a conceptual research framework that will combine DT, IoT monitoring, AI-based health scoring, and supply chain optimization.

The study focuses on four interrelated objectives: to create effective PdM strategies and the associated maintenance-based business models, to optimize the supply chains of components, and to create inclusive deployment pathways.

B. *Review Scope and Selection*

A targeted search was conducted across Scopus, Web of Science, IEEE Xplore, and Google Scholar for publications from 2021 to 2025. Search terms combined three target phases using boolean operators ("OR" & "AND"): primary target ("solar minigrid", "microgrid", "off-grid", "rural electrification"), next target ("predictive maintenance", "fault detection", "digital twin", "IoT", "health monitoring", "inventory integration"), and further target ("Business modeling", "machine learning", "deep learning", "supply chain", "inclusivity"). Studies were included if they addressed PdM for distributed renewable energy systems addressing our RQs, were peer-reviewed, and were published in English. Excluded studies addressing only utility-scale grids or non-electrical sub-systems, as well as whose experimental setup could not be independently reproduced.

Through this targeted search, we found 44 studies focusing on AI and ML techniques for microgrid PdM, fault detection, remaining useful life (RUL) estimation, DT modelling, IoT-based monitoring, and explainable AI. Supply chain, and maintenance logistics integration. Few studies on minigrid business models such as pay-as-you-go financing, and maintenance-as-a-service arrangements. Also, studies focused on inclusive deployment for underserved communities. Out of these 44 studies, eight were selected as primary references for this WiP paper based on direct relevance and conference reference limit.

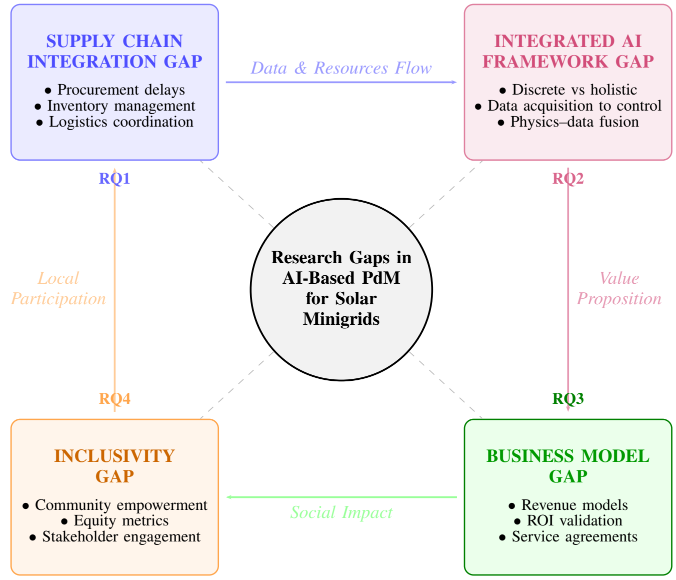

Fig. 1. Four interconnected research gaps identified through targeted literature review, mapped to corresponding research questions (RQ1–RQ4).

II. Research Gaps Identified

Through our targeted review, we found that literature treats fault classifiers, DT prototyping, IoT-based monitoring [5], and supply-chain integration as separate streams; no study bridges the full pipeline from sensor data to supply-chain action. Fig. 1 is visualization of our targeted research questions, and each question acts as a key barrier to the deployment of the other. Much of the current literature has less focus on off-grid solar minigrids with resource constraints. Scalability, interoperability, and practical implementation remains a challenge with most models being trained offline and not having adaptive learning systems to address environmental variability and system ageing. Further, the absence of standardised data sets and benchmarking procedures hinders reproducibility and comparative evaluation between studies.

A. Gap 1: Integrated AI Framework

The existing PdM studies consider monitoring, prediction as well as optimization as monolithic processes. Among the 44 reviewed studies, fewer than 3% is dealing with planning, design, and economic functions, with over 90% orienting their attention to the operations and maintenance [4]. While these themes are noted in the literature, they are addressed without the comprehensive frameworks required for systematic integration. Research on control data spans the entire value chain - from IoT sensing to feature extraction, and subsequent control actions, but remains fragmented [4]. Similarly work on monitoring and predictive capabilities demonstrates that while monitoring, diagnostics and early forms of DT implementation exist, they are still limited in scope; they rarely incorporate optimized decision-making measures or fully prescriptive components [3], [6]. Efforts in physics-based and data driven fusion have introduced hybrid simulation approaches, yet these developments remain relatively underexplored and insufficiently mature. This fragmentation prevents the development of unified, integrated systems able to manage minigrid health holistically, from initial sensing through to actionable intervention.

B. Gap 2: Supply Chain Integration

A significant gap identified is lack of integration between the results of PdM and supply chains logistics. Recent studies spend a lot of time in failure prediction and estimation of RUL and do not go further to make actionable decisions of supply chain [2], [3]. In terms of logistics coordination, multi-stage transit problems in remote areas are not considered, and coordination of crew processes is not related to PdM processes. The possibility of coordinated logistics between multiple minigrids is also never focused [7]. Li et al. [7] addressed offshore wind farm optimization with integration of component health controlling spare-parts inventory; this work adapts component health prognostics-driven inventory optimization approach for the solar minigrids.

C. Gap 3: Business Model Validation

Another gap is a lack of business models to support the AI-driven PdM in solar minigrids. Whilst technical improvements has been documented, the transformation of maintenance improvement to stable revenue streams and investor returns is a less focused area [7]. There is no empirical data on how maintenance enhancement can be related to financial returns, or there is no evidence showing the long term ROI of solar-powered minigrids. Similarly, there were no frameworks for availability-related service level agreements (SLAs) and maintenance-as-a-service models. The economic viability and scalability of AI solutions are not rigorously tested [4]. Even technologically successful PdM systems will not be able to

TABLE I
SUMMARY OF KEY REFERENCES SELECTED FOR WIP REVIEW, MAPPED TO RESEARCH QUESTIONS (RQ1–RQ4)

Refs.	Authors (Year)	Journal/Conf. Name	Type	Selection Rationale
[1]	IEA (2024)	IEA Report	Policy	Authoritative global energy access baseline; SDG7 context for inclusivity framing
[2]	Arafat *et al.* (2024)	*RSER*	Review	Most comprehensive ML-for-microgrid PdM taxonomy; justifies LSTM and anomaly detection choices
[3]	Ebrahimi *et al.* (2025)	*IEEE Access*	Article	Lab-validated DT+LSTM for microgrid fault detection; DC topology parallels proposed emulation layer
[4]	Ranawaka *et al.* (2024)	*Energies*	Scoping	Largest DT+AI scoping review (325 studies); confirms <3% of studies address planning, design, or economic lifecycle stages
[5]	Kayalvizhi *et al.* (2024)	*IEEE ICSSES*	Conf.	IoT-based real-time monitoring prototype for solar PdM; demonstrates sensor-to-cloud data pipeline for fault awareness
[6]	Padmawansa *et al.* (2023)	*Energies*	Article	Digital twin for battery cycle-stress estimation via Rainflow counting; applicable to BESS capacity planning & maintenance scheduling
[7]	Li *et al.* (2024)	*Renew. Energy*	Article	Only paper integrating health-driven inventory control with maintenance logistics in energy O&M
[8]	Onu *et al.* (2024)	*IEEE SESAI*	Survey	XAI (SHAP/LIME) for PdM; links interpretability to operator trust and inclusivity

Note: 44 papers were shortlisted (not included them all due to WiP 8-reference constraint):

spread and stand a long term without proven business models to support.

D. Gap 4: Inclusivity and Equity

The last gap is about equity and social inclusion. Our target review found very limited treatment of community empowerment, equity metrics, and stakeholder roles in Minigrid maintenance optimization, as the minigrids can serve rural agricultural livelihoods including irrigation and cold storage [1] in projects like UKRI-funded Smart SIP+ project in Bangladesh, which motivates this research. There are no systems to assess or guarantee fairness in sharing benefits with all the user groups, and technology development is still immersed in making decisions on design and deployment of technology without sufficient local participation. Little attention is given to technical literacy, multilingual interfaces, or cultural fit for rural operators. This is a key gap for solar systems targeting vulnerable communities, with the deployment of technology being in-line with social development objectives [1].

III. PROPOSED FRAMEWORK

To overcome the identified gaps, we propose an integrated framework, based on four functional and interactive layers for AI-driven predictive maintenance in solar minigrids which enables end-to-end PdM with supply chain integration. The framework architecture is shown in Fig. 2, and the software architecture is presented in Fig. 3.

A. Layer 1: Emulation Layer

The proposed framework for a laboratory-scale grid-connected solar photovoltaic (PV) power conversion system, implemented at the Renewable Energy research laboratory at Birmingham City University, UK. As expecting that this developed framework can be validated under a controlled setting.

The PV Emulator rated at a maximum power 1.5 kW and is used as the DC source to emulate solar panel characteristics. The PV emulator output is connected to a DC–DC boost converter, which steps up the DC voltage to the DC-link level required by the inverter. The boost converter power stage is designed to ensure stable current ripple and DC-link voltage regulation. The output of the boost converter is connected to the DC link of a single-phase inverter, where any DC load can be connected. The single-phase inverter is implemented using an H-bridge topology, with a line inductor (L-filter) to attenuate switching harmonics and improve output current quality. The AC output, is connected to a Rish Master-3440i Multifunction Single Phase AC Power Analyzer with 100 A Current Transformer for real-time measurement of voltage, current, power, and power quality parameters. Any AC load can be connected, and a programmable RLC load can also be plugged as well. All voltages and currents are measured using LEM LV 20-P voltage sensors and LEM LA 55-P current sensors to enable accurate real-time monitoring and control. All analog sensor signals and PWM control signals are interfaced with a National Instruments sbRIO-9607 controller and compatible FPGA-based C-series I/O modules.

The emulation method will allow quick prototyping and testing of PdM algorithms in controlled and repeatable conditions before deployment on the field.

B. Layer 2: Communication Layer

PdM requires real-time communication and should be reliable with low latency. Therefore, a two-protocol framework has been considered, comprising MQTT (Message Queuing Telemetry Transport) for lightweight publish-subscribe messaging to use in local sensor networks, with support to effectively gather data provided by wired sensors, and LoRaWAN (Long Range Wide Area Net work) for long Range communication over low-power devices, used for remote sensors (e.g. soil) and back up for minigrids when cellular connectivity is down. The hybrid approach to communication is responsive to the special conditions of off grid environments and is also

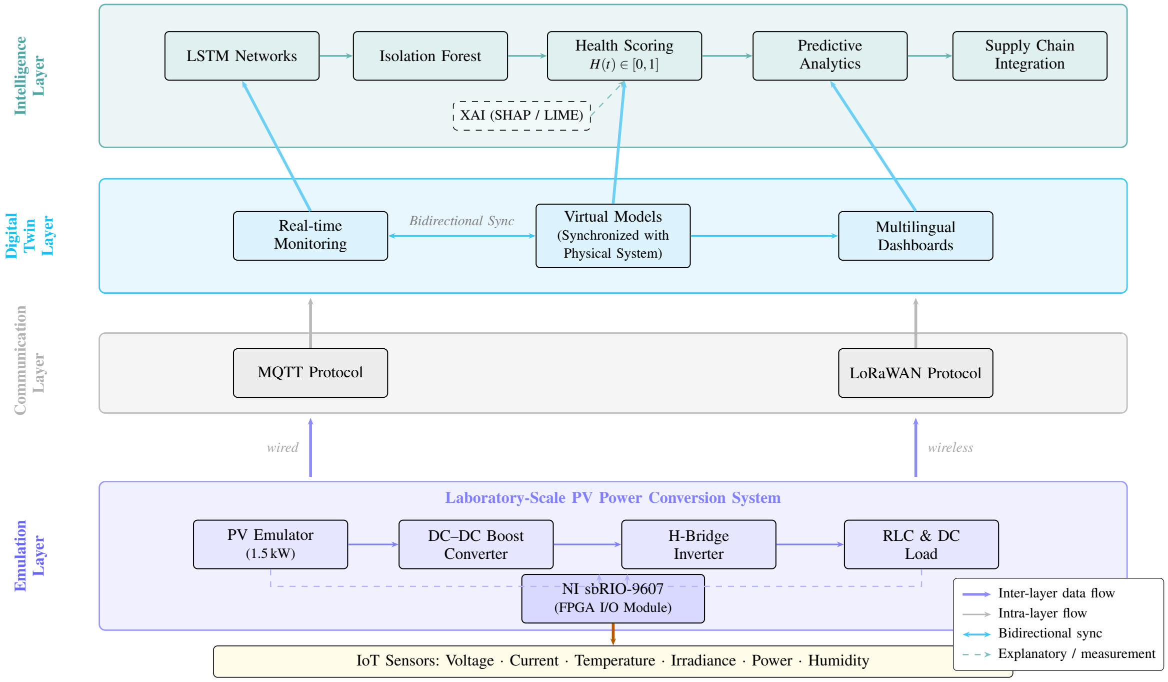

Fig. 2. Four-layer integrated framework architecture: Emulation (laboratory PV system), Communication (MQTT/LoRaWAN), Digital Twin (synchronized virtual models), and Intelligence (AI-based health scoring with supply chain integration).

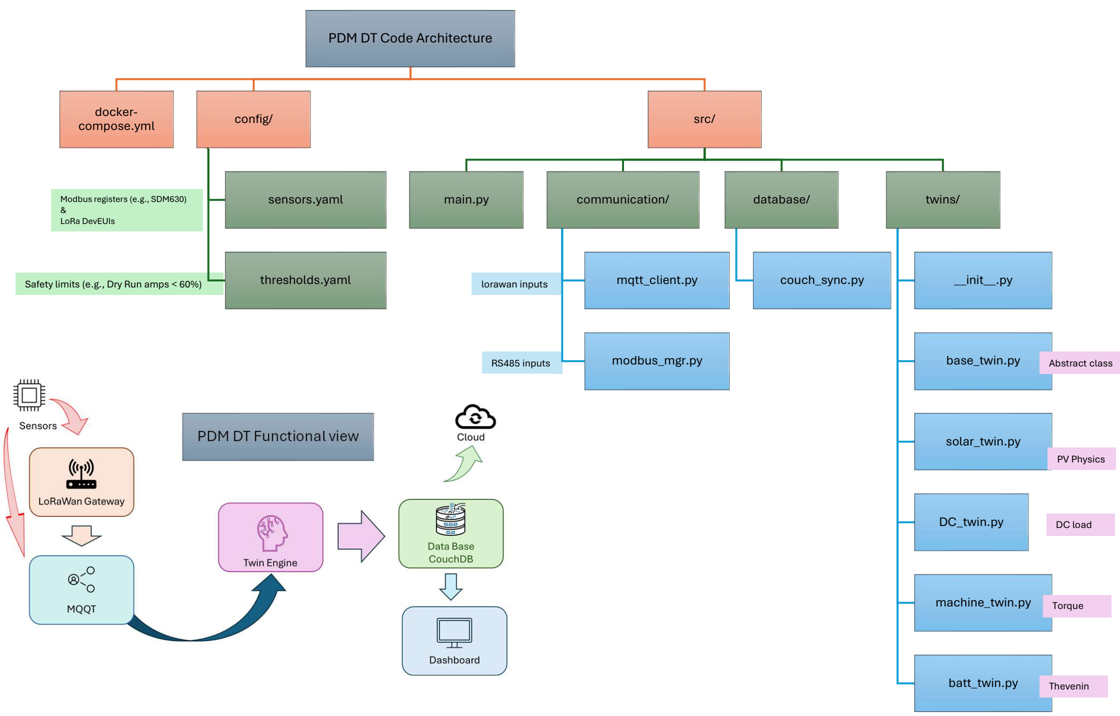

Fig. 3. Software and function architecture: Layer 2 corresponds to the communication modules, layer 3 to the digital twin modules, and layer 4 to the intelligence and decision logic.

able to respond to the needs of contemporary maintenance processes in time.

C. Layer 3: Digital Twin Layer

The DT not only copies the actual minigrid components, but, in conjunction with Layer 4, allows to interact with it. Continuous sensor tracking component physical state for component health, performance metrics and degradation indicators [5]. Physics based simulation models that are matched up with real world conditions that provide analysis of what-if scenarios. Padmawansa et al. [6] develop a microgrid DT estimating battery cycle stress and capacity for battery energy storage system (BESS) health assessment, while Ebrahimi et al. [3] demonstrate a hardware-in-the-loop (HIL) DT whose integrated Long Short-Term Memory (LSTM) classifier performs fidelity-validated fault detection on a laboratory-scale DC microgrid. These establish that physics-based virtual models can support both component-level health estimation and fault diagnosis within a maintenance framework. A practicable DT with multi-language interface for operators to support the rural people with limited technical knowledge. Thereby DT acts as the form of connecting physical assets with the intelligence decision-making framework [4].

D. Layer 4: Intelligence Layer

The intelligence layer has AI PdM capabilities [2]. It performs predictive and monitoring analytics by forecasting remaining useful life and failure probability. A unified health scoring system computes a health index $H(t) \in [0,1]$ that combines operational criticality, real-time sensor data, measured degradation curves and environmental stress factors as a normalized weighted aggregation:

$$H(t) = \alpha S(t) + \beta D(t) + \gamma C + \delta E(t), \tag{1}$$

where $S(t)$ is the LSTM-based sensor condition score, $D(t)$ the physics-based degradation state, $E(t)$ the environmental stress factor, and C the operational criticality factor, each normalized to $[0,1]$. The weights satisfy $\alpha+\beta+\gamma+\delta = 1$, ensuring $H(t) \in [0,1]$. XAI procedures (SHAP & LIME) give brief explanation of AI models used to non-technical and interested users for transparency and coaching [8]. The intelligence layer outputs are directly fed into the supply chain optimization modules converting health scores and RUL predictions into procurement warnings, lead-time adjustments and logistics decisions [7].

E. Supply Chain Integration Module

Within the proposed framework embeds an explicit supply chain integration module that converts AI-generated health scores and RUL predictions into actionable procurement, inventory, and logistics decisions [7]. When the health scoring system detects declining component condition, it automatically triggers procurement alerts factoring in spare-part lead times so that replacements are ordered before failures occur. Dynamic inventory optimization positions critical spare parts across minigrid locations based on predicted failure probabilities, degradation trends, and local operating conditions, reducing excess stock without compromising part availability. Logistics coordination synchronises maintenance schedules with crew routing and spare-part allocation so that technicians arrive with the correct resources. The module also supports multi-site coordination through centralised inventory management and shared logistics across multiple minigrids, reducing per-site costs and lead times.

IV. Expected Contributions

This study aims to provide inputs on three levels. In theory, it presents an overall conceptual architecture integrating IoT sensing, PdM, supply chain, and business model design for increasing ROI in off-grid solar minigrids. In practice, the framework offers a scalable PdM platform, supply chain integration algorithms between health predictions and procurement with a convenient multilingual dashboard interfaces and explainable AI for rural operator feasibility. In policy, this work recommends evidence based framework for implementing AI-driven minigrid by inclusive indicators of an equitable allocation of benefits for all community members.

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