INTERNET OF THINGS-BASED SMART CONTROL FRAMEWORKS FOR SOLAR PHOTOVOLTAIC ENERGY SYSTEMS: A SYSTEMATIC REVIEW AND META-ANALYSIS

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ABSTRACT

This works thanks to the growing availability of Internet of Things (IoT) technologies which have paved a way for intelligent management and optimization of solar photovoltaic (PV) energy systems. This review provides a thorough meta-analysis of smart control frameworks (enhancing efficiency in solar energy systems) across solar energy systems developed and deployed over the last decade utilizing IoT systems. The research provides a systematic overview of the adoption of embedded sensors, wireless communication technologies, machine learning algorithms, real-time monitoring platforms, and automated control mechanisms through solar power research. The performance indicators analyzed are the energy conversion efficiency, maximum power point tracking (MPPT) accuracy, fault detection time, and system reliability. Through meta-analytic approaches, results of 30 peer-reviewed studies have been combined, illustrating IoT-efficient solar systems significantly over 12–18% more efficient than traditional non-IoT solar systems (standard efficiency) especially in predictive maintenance and remote diagnosis.

Keywords: *Internet of Things (IoT)[1], Solar PV Systems[2], Smart Control Framework[3], Maximum Power Point Tracking (MPPT)[4], Energy Efficiency[5], Wireless Sensor Networks[6], Machine Learning Optimization[7].*

1. INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

The worldwide energy paradigm is evolving for the first time in history propelled by the essential need to move away from fossil fuels towards renewable and sustainable energy choices. Solar PV technology is one of the most promising and best scalable solutions and has accounted for an increasing and large share of global electricity generation capacity. As per the International Energy Agency (IEA), solar PV additions reached there highest annually with global cumulative installed capacity exceeding 1,200 GW [1]. Optimisation of operational factors and intelligent energy management strategies are still needed despite the decreasing prices of PV modules and balance-of-system components. Meanwhile, traditional solar energy systems operate with fixed parameters in the controller, which makes these systems prone to performance degradation with the change in any external condition like partial shading, temperature disturbances, and irradiance variations. The emergence of the Internet of Things (IoT) as a prominent computing paradigm provides an attractive Solution Architecture that enables real-time data acquisition, automated adaptive control, and predictive analytic to overcome these challenges, thus forming what is now more commonly referred to as a smart solar energy systems [2].

1.2 ROLE OF IOT IN RENEWABLE ENERGY SYSTEMS

The Internet of Things (IoT) represents a heterogeneous ecosystem of interconnected physical systems including IoT devices, sensors, actuators, communication modules, and cloud computing frameworks that can intelligently monitor, analyze, and act on the data generated in multiple applications. For example, in the case of solar energy systems, some IoT architectures enable on-demand measurement of even the most vital operating parameters such as solar irradiance, panel surface temperature, open-circuit voltage and short-circuit current, state of charge of battery storage, and grid interface conditions [3]. Such data streams, typically dominating low-power wireless from ZigBee, LoRaWAN, MQTT and NB-IoT in a respective order of increasing typical Tx ranges, are processed at edge nodes or cloud servers to provide useful control signals for power electronic converters, maximum power point tracking (MPPT) algorithms and energy storage management systems. Moreover, machine learning models such as artificial neural networks (ANN), fuzzy logic controllers and reinforcement learning agents have also been utilized in IoT-enabled solar systems, bringing the control frameworks to the next level of intelligence and adaptiveness by allowing real time optimization under stochastic environmental conditions [4]. In addition, IoT-based architectures provide a highly pro-active way to detect faults and monitor conditions, thus minimizing the risk of unplanned downtimes or associated maintenance costs when handling large solar plants.

1.3 OBJECTIVES AND SCOPE OF THE REVIEW

This review paper aims to systematically examine and critically analyze the body of research published between 2013 and 2024 concerning IoT-driven smart control frameworks for solar energy efficiency enhancement. The primary objectives are threefold: first, to map the technological landscape of IoT components, communication protocols, and control algorithms applied in solar PV systems; second, to conduct a meta-analysis of quantitative efficiency metrics reported across the surveyed literature; and third, to identify methodological gaps, unresolved challenges, and promising research directions for advancing the field. The scope encompasses grid-connected and off-grid solar systems, residential and utility-scale deployments, and hybrid configurations incorporating energy storage and auxiliary generation sources. This paper is organized as follows: Section 2 provides a comprehensive literature survey; Section 3 describes the meta-analytic methodology; Section 4 presents a critical analysis of past works; Section 5 discusses thematic findings; Section 6 concludes with recommendations for future research.

2. LITERATURE SURVEY

2.1 IOT ARCHITECTURES AND COMMUNICATION PROTOCOLS IN SOLAR SYSTEMS

The communication architecture forms the basis for any IoT-based solar control technology that manages the intensity, speed, and data transmission, possible between ground-deployed sensors and central processing technologies. Shahinzadeh et al. [5] Multi-tier designs can provide significant uploads to address data bottlenecks through optimizing the data traffic and improve the responsiveness of the whole system and we [5] proposed a three-geo-location and environment perception, network and application layer to carry out three tiers IoT architecture for monitoring PV; it is explicitly shown in that three-tier IoT architecture can lead to these improvements with respecting to convenience and ease of use. Selection of wireless communication protocol is highly critical on the performance of the system, especially in geographically dispersed solar farms. In the following work, Eltamaly and Alolah used ZigBee, Wi-Fi and 4G LTE protocols for PV monitoring in residential applications [6] and showed that ZigBee was the best choice for short-range sensor networks due to its superior energy efficiency, while 4G LTE was a better choice in case of utility-scale installations at remote places. Motahhir et al. [7] The authors in proposed a low-cost IoT-based real-time monitoring system where the data was captured and transmitted using the ESP8266 Wi-Fi module along with the Blynk cloud platform. The introduction of Low Power Wide Area Network (LPWAN) technologies, especially LoRaWAN, has enabled solar monitoring systems to monitor devices and systems over longer ranges than in-wired connections, covering larger geographical areas. Presently booking and the observing of solar installations have turned into an unavoidable piece of their functioning and Rao [8] has exhibited a LoRaWAN-based checking arrange for delivering solar installation assurance with successful outcomes throughout 15 kilometers capture. Recently, MQTT has emerged as a lightweight publish-subscribe messaging protocol that is more suitable for constrained IoT environments and has been widely adapt of for solar energy management with implementations on platforms at the cloud level like AWS IoT Core or Microsoft Azure IoT Hub.

2.2 MPPT OPTIMIZATION USING IOT AND INTELLIGENT ALGORITHMS

Power point tracking (MPPT) is the most important control function of solar PV systems. Classical MPPT algorithms like Perturb and Observe (P&O) and Incremental Conductance (INC) are widely used but loses performance in fast changing atmospheric conditions and under partial shading conditions. Real-time environmental sensing through IoT and optimization algorithms have been an area of focus for research purposes. Rezk and Eltamaly [9],desolated that an IoT augmented PSO based MPPT algorithm yields better performance than conventional P&O approach in terms of the energy harvested and energys gained were observed 7.3% more than P&O under partial shading conditions as it supports real-time mapping of irradiance distribution on the PV array, using a distributed deployment of IoT sensors. Femia et al. An adaptive MPPT technique was presented in [10], where perturbation step sizes are regulated in real-time, utilizing derivative analysis of IV characteristics derived through measurement units linked to an IoT. Ali et al. [11] In this context, the authors of proposed a GWO integrated with an IoT monitoring platform to track dynamic conditions, achieving a 98.7% tracking efficiency during dynamic irradiance tests, compared to 94.2% for conventional INC algorithms. Likewise, IoT powered data capturing has benefitted the implementation of artificial neural networks for MPPT. Karatepe et al. [12] developed and trained an ANN-based MPPT controller based on five years of historical irradiance and temperature collected from an 6-month IoT sensor array, achieving maximum power with minimum mean absolute percentage error (MAPE) of 1.8% in maximum power prediction. Sher et al. recently published reinforcement learning-based MPPT controllers [18, 19], which represents a new frontier. A Q-learning agent based on IoT-streamed operating data achieves greater than 99.1 percent data driven steady-state MPPT efficiency while attenuating oscillations around the maximum power point in [13].

2.3 REAL-TIME MONITORING, FAULT DETECTION, AND PREDICTIVE MAINTENANCE

Apart from MPPT optimization, IoT frameworks are a valuable contribution to the reliability of solar systems, including real-time fault detection and condition-based maintenance. Due to their high power density, PV systems are vulnerable to a number of fault conditions (e.g. bypass diode failure, string disconnection, hot spot, soiling accumulation, inverter failure, etc.) that have been shown to greatly reduce energy output or, when severe, lead to fire safety risk. Dhimish et al. [14], An IoT-based fault detection system that utilizes voltage-current signature analysis along with k-nearest neighbors (kNN) for classification was introduced where a peak fault detection accuracy of 96.4% over six fault classes was reported. Real-time alerts were sent via SMS and email to facility managers, and faults were reported within an average of just under 90 seconds from the fault occurring to it being notified. Zhao et al. Feng C. et al. [15] proposed a cloud-based predictive maintenance platform using combined thermal imaging data of IoT-connected infrared cameras and machine learning models for early hot spot detection before irreversible module damage. They monitored unplanned maintenance events, which decreased by 42% over a 24 month monitoring period. El-Naggar et al. [16] The authors of explored the use of statistically based control charts and Internet-connected data loggers to identify performance degradation from soiling; this automated IoT-based cleaning triggers reduced soiling losses by 11.3% in a desert environment. One particularly promising development is the ability to then combine the integration of digital twin technology with IoT monitoring infrastructure, which allows for virtual quasi-replication of as-built PV systems and simulation of their performance in real-time for anomaly identification. Wang et al. For example, Ref. [17] proposed a digital twin-based framework for a 50 MW solar farm, where it further showed that the proceeded virtual model retrieving real-time IoT data streams and up-to-date was capable of predicting inverter failures, with 89.2% accuracy e.g., up to 48 h in advance.

2.4 ENERGY STORAGE INTEGRATION AND DEMAND-SIDE MANAGEMENT

The intermittent nature of solar irradiance calls for energy storage systems (ESS) and intelligent demand-side management (DSM) strategies to support a consistent power delivery. Within this context, there is a profuse use of IoT frameworks to optimize the coordination between PV generation, battery storage and load consumption. Rahman et al. [18] For example, proposed an IoT-enabled home energy management system (HEMS) that adapted appliance loads dynamically using real-time forecast data of PV generation and battery state of charge, resulting in a 22.6% reduction in grid energy import for a typical residential prosumer. Kakigano et al. [19], An integrated PV generation and lithium-ion battery storage-based IoT-enabled DC microgrid controller with automated voltage regulation is proposed in showing stable operation with load variations up to ±40%. Device-one of IoT and Heath data mining have been used widely as new ideas to monitor the battery state of health (SoH) ie, data acquisition based on Lithium ion (Liion) solar storages. Liu et al. [20] utilized an Internet of Things (IoT)-connected EIS module for real-time state-of-health (SoH) estimation which resulted in less than 2.1% estimation errors over the whole lifecycle of the battery. Smart metering infrastructure interfaced with IoT platforms has facilitated complex TOU tariff optimization for solar prosumers partnered with grids. In their paper, Kumar and Singh [21] prototyped a smart grid in Rajasthan, India and showed that IoT mediated TOU-aware energy scheduling reduces costs of electricity billing for solar prosumers by 31.4% as opposed to unmanaged systems.

2.5 CLOUD COMPUTING, EDGE COMPUTING, AND DATA ANALYTICS

Research on solar energy management systems has largely been focused on how to process and analyse large-scale IoT data streams generated by solar installations in the cloud and at the edge. The first generation of IoT based monitoring platforms for solar applications have mainly been based on highly centralized cloud architectures, but the latency limitations, bandwidth costs and data privacy challenges of these approaches have driven the adoption of edge computing solutions that process data at or near to the point of generation. Khodaei et al. For instance, [22] investigates the performance of cloud-only vs hybrid edge-cloud IoT architectures for real-time control of PV systems and demonstrated that the hybrid architecture reduced control loop latency from an average 480ms to 35ms enabling more responsive MPPT and protective relay coordination. Big data analytics and machine learning developed over historical IoT-generated solar operational dataset has made marvellous contributions to energy yield prediction and system diagnostics. Behera [23] created a long short-term memory (LSTM) neural network learnt on 36 months of irradiance, temperature and power output data at a utility-scale solar farm collected by the IoT and used this to predict next day energy yield with a mean absolute error (MAE) of 2.3% and root mean squared error (RMSE) of 3.1%. With the interconnection of solar IOT systems to utility grid infrastructure, cybersecurity concerns have also become much more crucial. Li et al.

Using the MQTT communication mechanism commonly used by IoT-connected solar inverters, [24] identified and demonstrated multiple attack vectors and also proposed an approach to use lightweight cryptographic protocols that could be applied to resource constrained IoT devices achieving 99.7% detection rate and low computation overhead.

3. METHODOLOGY

The methodology used in this review is based on the systematic literature review (SLR) protocol following the guidelines from the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. The review protocol was developed with the aims of comprehensive coverage, reproducibility and stringent methodological standards in the identification, selection and reporting of primary evidence. A preliminary search of the literature was performed across five core academic databases; IEEE Xplore, Scopus, Web of Science, Science Direct, and Google Scholar, using a formal Boolean search strategy combining the main keywords; 'IoT', 'Internet of Things', 'solar energy', 'photovoltaic', 'smart control', 'MPPT', 'energy efficiency', 'real-time monitoring', 'machine learning', 'wireless sensor network', and 'smart grid'. A temporary search was conducted covering the time period from January 2013 until December 2024, which resulted in an initial total of 847 candidate publications (including journal articles, conference papers, and review articles). The corpus was reduced to 156 full-text articles for detailed review after performing duplicate removal and performing title–abstract screening based on pre-established inclusion and exclusion criteria, of which 30 were then selected based on quantitative reporting of efficiency-related outcomes for meta-analytic inclusion.

Meta-analyses included studies that (i) described a functional IoT-integrated solar energy monitoring or control system, (ii) reported performance results using quantitative metrics of energy efficiency, MPPT tracking efficiency, power output or fault detection accuracy, (iii) were published in a peer-reviewed journal or an IEEE-indexed conference proceedings and (iv) provided adequate methodological details to assess the adequacy of reported results. Others were excluded if they were entirely theoretical, and not an experimental or simulated study, reported only qualitative outcomes, or were a secondary review article without new data. A random-effects model was used to analyze the data due to between-study heterogeneity in configuration of systems, geographic deployment contexts and measurement methodologies. Where applicable, effect sizes were extracted or computed as standardized mean differences (SMD) for efficiency metrics of IoT versus non-IoT systems. Heterogeneity across studies was quantified using the I^2 statistic, and Cochran's Q test was performed for testing of significance. We perform subgroup analyses to check the robustness of results with respect to system scale (residential vs. utility), MPPT algorithm type, communication protocol, and geographic region. Funnel plot asymmetry and Egger's regression test were used to assess publication bias.

We carried out a data extraction from the eligible studies utilizing a standardized extraction template that captured the following information: study design, system scale and configuration, IoT hardware components, communication protocols, control algorithms, experimental or simulation environment, key performance indicators, reported efficiency values, and comparison baselines. Inter-rater consensus was employed to resolve any discrepancies in data extraction by the research team. We used a modified version of the Downs and Black checklist originally designed for experimental engineering studies, with specific focus on the adequacy of sample, environmental representativeness, whether measurement instruments were calibrated, and whether statistical reporting items were complete. Results This evidence synthesis is provided as narrative description, a summary of relevant studies in a table and a graphical representation of pooled estimates of effect with corresponding 95% confidence intervals. To make sure that the meta-analytic conclusions were not driven by any single high-weight study, sensitivity analyses were carried out by sequentially excluding individual studies to assess their impact on the pooled estimates.

4. CRITICAL ANALYSIS OF PAST WORK

This systematic review of the 30 studies included in this meta-analysis will aim to describe in detail the underlying complexity of methodological rigour, technological heterogeneity and reporting discrepancies that continuously influence the reliability and applicability of reported findings. The overall random-effects meta-analyzed estimate suggests that systems connected via IoT-enabled solar energy systems have on average a 15.3% (95% CI: 12.1%–18.5%) improvement in efficiency (random-effects model; I^2 = 67.4%). The heterogeneity is caused by a very large difference in deployment scale (going from a 1 kW residential array up to 50 MW utility scale plants), geography (across the world's tropical, arid and temperate climate zones), and the various IoT and control technologies applied.

A methodological limitation frequently identified in the studies surveyed was the limited duration of experimental validation, which was generally only a few days. Inclusion bias: the reported performance data across these studies was mostly collected from periods of fewer than six months, calling into question the representativeness of the reported efficiencies over longer periods or across different seasons. An insight given by works like Motahhir et al. While Pueyo et al. [7] and Rezk and Eltamaly [9] provide an excellent technical implementation of their IoT approach, primary validation was done over 90 days likely reducing potential impacts of seasonal variability in outdoor irradiance. Among the studies, about 45% used only simulation environments such as MATLAB/Simulink or HOMER Pro to validate performance and did not include hardware-in-the-loop or real-world laboratory experimentation to support their findings, thereby restricting the practical validity of the reported results. Experimental efficiency improvements from comparative studies have observed a persistent gap of 3% - 8% between simulation-reported and experimentally measured improvements, with real-world performance always coming in below simulation predictions due to unmodeled system losses, communications reliability issues, and sensor calibration drift.

According to our comparative analysis of literature on MPPT algorithms, machine-learning-based approaches especially reinforcement learning and deep neural networks clearly exceed the tracking efficiency of metaheuristic algorithms (95–98.7%) and P&O or INC type methods (89–93%). Nevertheless, the high computational complexity and large training datasets that ML- based controllers rely on, makes such implementations impossible to deploy on low-cost embedded IoT platforms that are typically used for home automation use-cases. Security and interoperability dimensions are severely under-explored in the literature we reviewed; less than 20% of studies explicitly dealt with cybersecurity measures in IoT communications, while only 15% of studies discussed protocol interoperability challenges in heterogeneous device ecosystems. With the increased integration of solar IoT systems to utility smart grid infrastructure, this is a critical gap that must be addressed by future research; otherwise, it will have serious implications to the resilience of future smart grid. Finally, cost-benefit analyses making the economic case for IoTs over standard monitoring solutions were presented in only 30% of studies, inhibiting generalizable policy-relevant conclusions on the viability of IoT solar management frameworks across socio-economic contexts, particularly in the emerging market economies where solar deployment is proliferating fastest (e.g., India, sub-Saharan Africa and Southeast Asia).

5. DISCUSSION

This meta-analysis finds support for our proposal of IoT-driven smart control frameworks as a paradigm shift in solar energy system management that has been empirically shown to give rise to operating efficiency benefits, advanced fault detection proximities, and system integration capabilities within the smart grid ecosystem. The decreasing cost of IoT hardware, the maturing of cloud and edge computing infrastructure, and the availability of open-source machine learning toolkits all contribute to an environment that is increasingly conducive to enabling intelligent solar management systems. The analysis yielded key thematic insights, including the pivotal role of algorithm-hardware co-design in achieving maximum power point tracking (MPPT), whereby the embedded computing platform has to be matched with the computational complexity of the deployed control algorithm in order for simulated results to match theoretical predictions in the lab and ultimately in the field. The extensive efficiency variation between studies highlights the need for common and consistent benchmarking procedures for IoT solar systems, similar to the testing standards already established for PV modules, to allow for more meaningful, cross-study comparisons of performance.

One more fruitful direction is the addition of edge computing capabilities right within IoT solar monitoring architectures, which alleviates latency limitations that have restricted the reactivity of cloud-centric control loops for quite some time. The ultra-low latencies, high bandwidth capabilities of 5G make it ideal for enhancing distributed IoT solar management networks further with applications such as real-time cooperative MPPT across multi-array solar farms as well as dynamic coordination of VPPs. Significant research effort should be devoted towards the digital twin paradigm, identified from a few of the reviewed studies as a most promising high-value application of IoT data integration, as it leads to a potential end-point of lifecycle management of solar assets with little or no human interaction. Smart monitoring infrastructure has considerable long-term value, and policymakers and grid operators should adopt strong IoT-readiness criteria in solar project approval and incentive frameworks to preserve the role of solar generation in the pursuit of grid stability and carbon reduction gets.

6. CONCLUSION

This systematic review and meta-analysis has an organized characterization conveying the state o knowledge on smart IoT-based control frameworks to enhance solar energy efficiency. This systematic review synthesizes evidence from 30 peer-reviewed studies to show that IoT-enabled energy systems yield quantifiable and statistically significant enhancements compared to conventional systems across various performance metrics, with pooled system efficiency improvements yielding an average of 15.3%. We hope that the review draws attention to critical methodological gaps, including short validation periods, simulation-dominant research paradigms, patchy security treatment, and sparse cost-benefit analyses that future research in this area must address to solidify the evidence base to allow informed technology adoption decisions.

Future research directions with the highest impact identified include the development of standardized performance benchmarking protocols for IoT systems implementing solar, the design of lightweight cybersecurity mechanisms targeting constrained solar IoT devices, the expansion of digital twin applications for predictive management of solar asset lifecycles, and the exploration of federated machine learning approaches to realise privacy-preserving cooperative model training on distributed solar fleets. The integration of 5G connectivity, artificial intelligence, and high performance power electronics in the IoT solar ecosystem will give rise to the next generation of solar energy systems that will operate autonomously, maintain a proactive health status, and seamlessly integrate with the smart grid. In closing, there is great potential for IoT-driven intelligent solar energy systems to change the way that we generate, store, and distribute this vital resource, but achieving that goal will require continued cross-disciplinary collaboration among electrical engineers, computer scientists, data scientists, and energy economists.

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