From Sensor Streams to Grid Decisions: A Critical Review of AI-IoT Integration in Renewable Energy Systems

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How to Cite this Article:

CHAUDHARI, R. (2026). From Sensor Streams to Grid Decisions: A Critical Review of AI-IoT Integration in Renewable Energy Systems. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(05). https://doi.org/10.55041/ijcope.v2i5.594

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Abstract

But generation capability is no longer necessarily a constraint for integration of energy. That's more an interpretation and a quick response, however, than maths; They are constantly monitoring a number of thousands of devices across the country and understand the impact of the weather, and can also act quickly in case of failures to ensure the reliability of the grid. This article delves into the combined powers of Artificial Intelligence (AI) and the Internet of Things (IoT) to tackle this challenge. It is believed that technology for interconnection of PV plants, wind power, storage, EV charging stations, smart meters and buildings will be IoT and this same technology will serve as the basis for the operationalisation of the AI as a collection of predictive, diagnostic, optimising and controlling techniques. The paper does not so much describe applications one by one; it gives some indications regarding the steps to take in getting raw data, and in making consequential decisions. No longer integration of (renewable) energy is limited by generation capacities; integration of energy is about renewable energy forecasting, predictive maintenance, the operation of microgrids, EV charging coordination, smart-home energy management and much more. But this is more an opinion and a hasty answer than maths. Constantly monitoring thousands of devices throughout the country, knowing how the weather affects them and being able to swiftly respond to ensure the reliability of the grid. This article delves into the combined powers of Artificial Intelligence (AI) and the Internet of Things (IoT) to tackle this challenge. Technologies for linking PV plants, wind turbines, storage systems, EV chargers, smart meters, buildings are presumed to be IoT based and the operationalization of the AI based forecasting, diagnostic, optimization and control are expected to be built on the same technology. The paper does not so much describe applications one by one; it gives some indications regarding the steps to take in getting raw data, and in making consequential decisions. This encompasses renewable energy forecasting, predictive maintenance, microgrid management, EV charging management, and smart-home energy system management, along with edge intelligence, federated learning, and digital twins and block chain for energy markets. The result of this is that the value of the AI-IoT system is not truly created with the open AI-IoT system, which is connected via sensing, inference, control and governance. However with labelled data devices don't recognize, no explanations of reasoning of the model, no usable audit track of controls etc. predictive accuracy is not enough. Remotely deploying such things is thus enabled in parallel with researching models, architectures and systems that are standards-aware,

immediately ready for use of benchmark datasets that have been field-tested, adopt a physics-informed learning perspective, and provide a means of verifying that digital twin models are correct and that they are produced by tools that can analyze the computational complexity of operating a renewable-dominant grid over its entire life cycle.Index Terms

AI, IoT, renewable energy, smart grid, edge AI, digital twin, predictive maintenance and demand response and electric vehicles.

Each of these will be introduced, including some details.Each will be explained, and there will be some explanation. The result of this is that the value of the AI-IoT system is not truly created with the open AI-IoT system, which is connected via sensing, inference, control and governance. Nevertheless, with labeled data, devices don't recognize, model reasoning is not explainable, there are no usable audit track of control operations, etc. predictive accuracy is not sufficient. The paper thus recommends research on systems, architectures and models that are standards-aware, ready for immediate use of benchmark datasets that have been field tested, at the same time enabling deployment of these things at the edge; that enable a physics-informed learning approach; that offer means to verify that digital twin models are accurate and that they are created using tools to analyze the computational complexity of operating renewable-dominant grids over their entire life cycle.Index Terms

Artificial intelligence, Internet of Things, Renewable energy, Smart grid, Edge AI, Digital twin, Predictive maintenance and demand response, and EV's.

Introduction

Energy transition is happening the most concretely at the distribution edge. Today, PV arrays are installed on the roof, PV generation facilities have increased in size, a few houses with a demand response capability have been integrated, wind is being integrated, battery storage is becoming available, EV charging stations are being installed, and microgrids are being deployed more and more. Generation of renewable electric power, scaling up electric storage, electrification, and demand side flexibility play a fundamental role in all pathways to climate mitigation, including all major global energy assessments [1, 2, 3]. The engineering problem is how to truly manage a system comprised of the most dynamic resources, spread across geographical locations, in a weather dependent and typically disjoint and varying owner context.

The basics of renewable resources differ vastly from that of the synchronous generators. The dispersed energy resources can alter the flow of energy completely, wind power can fluctuate on a number of time scales, and the PV generation can load or unload in minutes. These characteristics manifest themselves at high penetration as voltage excursions, network congestion, protection coordination uncertainties, higher reserves, islanding problems and market scheduling inaccuracies. IEEE Std. The integration of DER is a problem not just a power electronics problem, this is the same perspective as the Standards community in terms of interoperability and communications [4] [5].

AI and IoT are two different worlds in Residential A&D, but for renewable systems, there doesn't appear to be any difference. On a continuous basis, it is difficult to monitor the operational signatures of an asset, so this is what IoT devices are able to accomplish. These signatures are then processed with AI algorithms to predict, alarm on faults, schedule dispatch and set control and send maintenance recommendation. It's not sufficient to merely ‘see' the data coming in from the sensor, it needs to be something with a managed feedback loop through which sensor data can be acted upon, there is accountability, it's understandable and it can be changed.

The aim of this article is to make three contributions. Firstly, it puts the synergy of AI and IoT in place as a cyber-physical layered architecture from the physical sensors and communication systems to governance. Second, it examines the primary application areas, examining the added value of connecting sensing with AI techniques. Third, it plots roadblocks to the adoption of a large number of models that fall outside the realm of simulation or pilot testing, and highlights the importance of data quality, interoperability, cyber security, model explainability and real world validation.

Review Scope and Method

The next method of narrative review was used in this article. Because the number of datasets and duration of study time, reported in the studies reviewed, varied greatly, as well as the assumptions of control, types of devices, and measures used to test devices, a statistical meta-analysis was not attempted. Rather it has been divided by the engineering function being imbued by the integration of these technologies: (AI-IoT) Generation Forecasting, Communication and Interoperability, Demand reduction, EV Charging, Cyber Security and Privacy, and Newer Architectural Approach like Edge AI, Federated Learning, Digital Twin and Energy Markets on Blockchain.

The review is done in the light of the three sources. From a policy and a planning perspective, the discussion on energy transition begins with energy transition reports as the basis for the discussion on how to operate a grid with a high renewable content [1, 2, 3]. There are several standards and interoperability documents that detail the “how” of a real deployment of such an AI-IoT systems [4, 5, 6]. The studies are conducted based on the above technical studies to understand how the different industries integrate AI and IoT [7, 8, 9, 10, 11, 12, 13, 14, 15, 17]. It focuses on the design of the system and suitability for field operation instead of drawing out maxims of precision from individual studies.

AI-IoT Architecture for Renewable Energy Systems

The integration of AI with IoT can be imagined as a supply chain in the renewable energy industry.AI-IoT integration can be thought of as a supply chain in the renewable energy sector. All by itself, a sensor reading doesn't mean much, it needs to be time-stamped, sent, contextualised, interpreted and finally translated into an operation, which takes into account technical constraints and rules. The scheme provided below is, therefore, an abstraction and a modified physical layout may be adopted.

Perception and Device Layer

The different layers of the device are smart meter, PMU, irradiance sensor, anemometers, thermal camera, vibration sensor, battery management system, protection relay, EV charger, building automation sensor, household appliances. The crucial thing is how much coverage do all the sensors provide, not the number of the sensors in a network. Four categories of information are required for any renewable resource: environmental, electrical production, equipment condition and local operating condition. Lacking any of those leaves room for ambiguity from downstream AI work: If PV production drops off, it could be due to clouds, soiling on the PV panels, partial shading, inverter derating or sensor failure. If all four data streams are not provided, it will be hard to differentiate amongst the four.

Communication Layer

The communication layer is used for communication between the field devices and to the gateways, the edge nodes and cloud platforms, utilities and aggregators and even system marketplaces. Should not be preference based on protocol. Should be based on a control requirement! Protection signalling and inverter control involves less latencies, highly reliable exchanges and is okay with slower reporting for fleet analytics and planning. Other communication protocols like MQTT, CoAP, DDS, AMQP, OPC UA or XMPP are proposed to be applied in smart-grid and IoT applications but they can be used depending on the type of the payload, tolerable latency, strength of the device processing power, and security concerns [7, 8, 9].

Edge, Fog and Cloud Processing Layer.

Cloud infrastructure plays a great role in longterm forecasting, scaling model training, analysing historical data and crossfleet optimisation. When the central processing is not safe, viable, or possible because of communication latency, data privacy, and/or resilience, edge and fog resources are critical. The use of a workable division relies on edges devices being used to perform localised tasks with time requirements, such as detecting any inverter issue, whilst cloud systems are used to perform coordinated tasks with time requirements across larger populations of assets. This boundary is not hard set, but rather changes due to the costs of communication, complexity of the model and the consequences of being slow to respond.

This layer is called Intelligence and Decision Layer. This is the Intelligence and Decision Layer.

These algorithms include machine learning, deep learning, reinforcement learning, combinatorial optimisation, anomaly detection, probabilistic forecasting and rule based control logic are all included in the intelligence layer. The selection of a model should not be treated as an order of preference - more sophisticated models are not necessarily more appropriate. When training data is limited and interpretability is important it is worth the use of random forests, support vector machines, gradient boosting, and regression methods. Temporal relationships, spatial relationships, or network topology are the primary source of predictive information in problems, then LSTM, convolutional, transformer and graph-based architectures are the most appropriate. Reinforcement learning can be a hugely powerful tool for EV charging coordination, HVAC dispatch and storage management, but before one is even attempted, fully constrained, simulated extensively and reviewed in a structured format by operators.

The appropriate application layer use and control.Use and regulation of application layer.

The application layer is where all model outputs become real – such as a summary of energy forecasts, dispatch schedules, a maintenance work order, a signal for voltage regulation, a demand response instruction, a settlement record or an asset lifecycle decision. Ultimately, the governance layer of the system—from cybersecurity to privacy safeguards, accountability to the regulatory level, model validation to data ownership, human oversight to safeguards—will determine whether those outputs can be put to good use. Even when a model has good statistical performance, an explanation of the reasons for a model can be provided to an operator; good data sources for the model inputs can be located and/or a wrong control action can be recovered if it is shown to be wrong.

Functional Stack for AI-IoT Integration in Renewable Energy Systems

p0.27 p0.30 p0.19 Layer	Main role	Renewable-energy examples	Key risk
Perception	Sense physical and electrical states	Smart meters, inverter telemetry, irradiance sensors, wind sensors, battery sensors, EV charge logs	Sensor drift, missing data tampering
Communication	Move data and control messages	MQTT/CoAP for lightweight telemetry, DDS/OPC UA for industri exchange, IEC/NIST-aligned interfaces	Latency, interoperability, insecure links
Edge/fog/cloud	Process data at suitable location	Local fault detection, feeder-level optimization cloud model training	Compute cost, bandwidth vendor lock-in
Intelligence	Forecast, classify, optimiz and control	PV and wind forecasting, load prediction, predictiv maintenance, RL schedulin	Poor generalization, explainability gaps
Application	Deliver operational value	Microgrid control, EV charging, demand respons	Deployment complexity, unclear business case

		asset management, energy trading	
Governance	Assure trust, compliance, and resilience	Privacy controls, cybersecurity, model audit human-in-the-loop operation	Liability, regulatory uncertainty

AI Techniques Used in Renewable AI-IoT Systems

Machine Learning for Forecasting and Classification

DL works best when patterns in the data are more easily described using only more complex models. Due to the time-varying nature of resource conditions, wind and solar time-series forecasting is done using LSTM and gated recurrent networks. The convolutional models are most suited for sky images, thermal images and spatial sensor arrays. In power network systems the topology affects the relationship between the voltage and current, as well as the power flow, which makes this situation explained by graph based models natural. The restriction to them is not theoretical, but practical, as they typically require a larger dataset, more computing power and more supervision of their operation if there are changes in the operating environment.

Deep Learning for Temporal and Spatial Patterns

DL is most persuasive when the data exhibit patterns which are more complex than those of simpler models. In addition to the time varying of the resource condition, it is selected to forecast the time series both wind and solar energy, for which calculation is performed by LSTM and gated recurrent networks. Convolutional models are effective when used with images of the sky, thermal images, or spatial sensor arrays. This is due to the topology of power networks, which affect the link between voltage, current, and power flow, which explains the choice of model type: graph models. The limitation to them isn't imitative, but practical: they normally need an extra large set of input information, a fair bit more computer horsepower and a fair bit more supervision of their operation if there are changes in the operating environment.

Reinforcement Learning and Optimization

RL is necessary because there are a lot of energy decisions that can take place in a row. Now, the charging decision will impact the loading of the transformer, battery condition, the satisfaction of the user and future opportunities. This includes energy management for the HVAC systems and storage dispatch, in addition to micro grid energy management. In [15] model-free deep RL, combined with stochastic EV pricing and user behaviour has been applied to real-time EV charging. But, RL is not an independent solution to replace the conventional control. It should be explicitly bounded in grid applications, be able to be simulated away from Internet, have safety filters and explicit human override path.

Hybrid and Physics-Informed AI

Models which are just based on data are weakest when the system is in a state where it has not been trained for. Typical examples are rare weather events, reconfiguration of feeders, inverter failures, and disruption of the market. The drawback of this is that they cannot be used to model physical constraints, power-flow relationships, equipment limits, or weather models. This is where hybrid models help. For renewable systems this is a good direction of travel since many constraints are known. The research question is to ensure that the models can be used as models and not become a demonstration of too much complexity.

Federated and Explainable AI

Data from the smart meter, building and EV can offer insights into the activities occurring in the home, and into the movement and activities within the business. One partial solution that is proposed is federated learning, in which the model is trained at scattered places, instead of the raw data at the places. The usefulness of it relies on efficient communication, resilience against tainted updates, and performance when non-identical local datasets exist. It is also important to explainability. Curtailment, switching, charging delay and demand response are models' recommendations, and operators should not only know this, but they should also know WHY they are recommended by the model! The word is “explanation” but in this context it goes hand in hand with accountability.

Application Domains

Machine Learning for Forecasting and Classification

Traditional ML methods retain practical relevance in utility environments where datasets are often small, incomplete, or gathered under shifting operational conditions. Random forests, support vector regression, gradient boosting, k-nearest neighbours, and decision trees see regular use in PV output forecasting, load prediction, equipment classification, and fault identification. The solar forecasting literature makes one thing consistently clear: predictive accuracy depends as heavily on forecast horizon, sampling frequency, meteorological inputs, and local climate conditions as it does on the algorithm itself [10, 11]. Load forecasting follows a comparable pattern — models perform meaningfully better when weather variables, calendar effects, occupancy behaviour, and historical demand figures are treated as interdependent inputs rather than fed in separately [13].

Deep Learning for Temporal and Spatial Patterns

Deep learning is most persuasive in situations where the data carry structures that simpler approaches cannot adequately capture. LSTM and gated recurrent networks are widely applied to wind and solar time-series forecasting, since resource conditions evolve continuously over time. Convolutional architectures are better matched to sky imagery, thermal camera feeds, and spatially distributed sensor arrays. Graph-based models suit power network problems naturally, given that network topology directly governs voltage profiles, current flows, and power distribution. The limitations here are largely practical: deep learning models typically demand larger training sets, greater computational resources, and more attentive monitoring whenever the operating environment shifts from what the model originally learned.

Reinforcement Learning and Optimization

Reinforcement learning warrants particular attention because many energy management decisions are inherently sequential. A charging decision taken at one moment alters transformer loading, battery state of charge, user experience, and the flexibility available in subsequent time steps. The same reasoning extends to storage dispatch, HVAC scheduling, and microgrid energy balancing. Model-free deep RL has been applied to real-time EV charging under conditions of uncertain prices and unpredictable user behaviour [15]. That said, RL is not a straightforward substitute for established control methods. Grid applications require explicit constraint enforcement, extensive offline simulation, safety filtering mechanisms, and well-defined procedures for human intervention when the policy behaves unexpectedly.

Hybrid and Physics-Informed AI

Purely data driven models are the least “survivable” if the conditions under which they are operated are not well known from the historical data. Typical examples are extreme weather conditions, changing feeder topology, fault in the inverter and sudden market disruption. Hybrid models are introduced to overcome this limitation to include known physical parameters, power-flow equations, equipment operational limits or known meteorological relationships in the model. On all but the renewable systems this is even easier to grasp for the following reasons: The constraints that apply for renewable systems are known analytically for a large portion. The challenge in the real world is to make such models tractable – usable to show or demonstrate functionality without failing to produce an operational model and result on an operational problem.

Distributed and interpretable AI.Distributed and Interpretable AI.

There is a lot of information that can be gained from smart meters, residential buildings and electric vehicles that can reveal daily activity in any household, the patterns of their travel and commercial activities. One of the partial solutions is to achieve distributed training of common learned models without collecting raw data in the central location: Federated learning. It depends on its ability to communicate overhead, robustness to corrupted or manipulated local updates and stable performance when working on sites with varying data distributions. But there is also the issue of explainability that is highly in demand. It is not enough for an operator to receive a number for someone on a prediction, the operator must also receive the reason for the recommendation for curtailing the model, and the recommendations for switching, charging delay or demand response actions. Whereas, it is directly tied with the capacity to describe the reasoning behind a choice in this domain and the ability to allocate blame for its repercussions.

Application Domains

Current status of Solar and Wind Forecasting.

The most obvious usage of AI-IoT is forecasting; the fluctuation of renewables can be notified and forecast, and even many years in advance of it ever being a problem for grid operations. Data included in the PV forecasting includes history of PV generation, present PV measurement/monitoring of irradiance, analysis of temperature and humidity measurement, satellite data, images of the sky, from the sky cameras, and numerical weather prediction outputs. Combining wind speed and direction values, pressure, turbine telemetry and the output of meteorological models allows wind forecasting to be accomplished. The lower the reservoirs, the better the forecasts, the higher the amount of unit bids with the lower the amount of curtailment. There is agreement in the literature on this fact that the choice of forecasting method does not dominate the different time periods and the climatic conditions, much less the various configurations of a plant [11, 12]. The salient lesson here is that local IoT instrumentation can be meaningful, just because it can map the level of local predictions to the behaviour of the local assets.

Identification, prediction of faults by predictive maintenance and fault detection techniques.

Another field where continuous sensing has an impact on changing decisions is condition-based maintenance. The wind and solar installations are distributed all over the world, in extremely harsh weather conditions and too distant to be monitored on a regular basis. Monitoring of vibration signatures, operating temperatures, power quality indicators, insulation resistance, behavior of the inverter while switching and mechanical loading can be done using sensors. The AIs can then identify accurately if there are any deviation from the normal behaviours and how much useful life is remaining on a part. In the wind application, this can be used to detect gearbox, blade, generator or bearing faults, and in the PV application, it can be used to detect soiling, partial shading, module mismatch, thermal hot spots, and inverter degradation. Its benefit is not just what it can save you on asset maintenance costs, but when he can make sure that your assets are available when the renewable resource is most productive.

Smart Grid/ Microgrid Control

AI-IoT coupling is closest to real time in the context of smart grids and microgrids. Sensors and metering equipment enable the current situation of the network to be recorded, while algorithms make forecasts about networks and their possible changes and assist in decision making process of the network as to corrective or preventive action. It can be used for voltage regulation, feeder switching, storing dispatch / system islands, system restoration and deployment of a demand response programme. They are all interconnected with equipment from utilities, technology vendors, aggregators as well as with end customers, which makes for standards-compliant communication as a prerequisite [4, 8, 11]. A coordinating problem that is of particular explanatory importance is the adaptability (flexibility) of the local incremental generators to meet various levels of local load, available storage and generation levels.One such manifestation of the problem exists when constraints of local generators' flexibilities and local loads should align with the capabilities of the surrounding power grid, a weather event occurs, the local consumption pattern changes, and the connection between the two power systems is unpredictable.

EV Charging Coordination

The latter is an interesting ‘use case', particularly if it is to be used for selling electricity to EVs and as such the charging process to provide a mechanism to make the grid flexible. With little or no coordination, uncoordinated charge can even exacerbate greater evening peaks, plus load the distribution transformer. An intelligent scheduling system can be implemented to rearrange the electricity demand to the time when renewable energy resources is abundant to lower electricity costs, and to allow room for network system constraints. AI models might estimate a level of charging EV demand, as well as predicted departures and probabilities of price sensitivity and availability of renewable outputs. These estimates are then translated in to the schedules with the physical interface, by use of smart and connected charging infrastructure. As the problem is quite sequential, but the search is speculative, it also seems possible to solve with RL and optimisation methodology. Providing a pleasant experience to the user should not be a matter of chance, but a part of the problem itself [15].

Technology solutions supporting the concept of a "Smart Home" and Demand-Side Management.

On the household level the two indicators of Technical performance and Resident acceptance are interchangeable. The different elements of a smart-house, such as occupancy and environmental monitoring sensors, sensitive controllable appliances, programmable thermostats, on-roof-top PhVs, battery storage units and EV charger are interconnected by a home energy management system (HEMS). AI can be used to subdivide load signatures into monthly, quarterly and annual patterns; to predict the whole household load; to optimise the operation of HVAC systems; and to automatically control the load depending on tariffs (or grid operator signals) which change over time. The study conducted on IoT in the HEMS shows the enormous potential for the creation of comfort, safety and energy efficiency [14]. Design collision occurs when the occupants feel that an energy management system is more of a nuisance than welcome, is capricious in some form, or apathy towards the need of the occupants for comfort.

Digital Twins & Lifecycle Management.

The value of operators is high when they can test decision on a non-dangerous way ahead of the placement of steps in the field with digital twins. Both can be a part of a simulated wind turbine (or simulated PV array, distribution feeder, simulated micro grid or large scale simulated grid zone based on live data from all viewing devices, etc.).Here, the simulation could represent either 1 or more of the following renewable energy devices: wind turbines, PV plants, distribution feeders, microgrids or a part of the grid, along with actual data from each of the looking devices that exist in the selected area. The digital application of the digital twin to the smart grid has three significant obstacles and is about to overcome, according to recent study, which was classified into three main problems: IoT connectivity and storage of relevant data, AI [17] and cybersecurity measures. One of the consistent challenges is to ensure that the twin accurately represents the behaviour of the system – if it does not, then this may pose a risk.

What is blockchain?What is Decentralised Energy Markets (DEM)?

When one sees papers about renewable energy, one's initial thought would necessarily be on ‘blockchain': the solution to so build trust and automate settlements. Storing electricity, logging renewable energy certificates, settling electricity transactions in the microgrid, processing payments for EV charging, and flexibility markets. In IoT context the trading engine creates the trading ‘Proof of Evidence', whilst the price forecasting/price calculating of the ‘Market Crystal' is achieved by the AI system. But don't equate including blockchain as part of systems of energy as the norm of a design. If the blockchain cannot provide the same alternative facilitation systems, this situation may have negative implications for the blockchain's performance [18, 19] as all of these factors have a detrimental effect on the performance of the blockchain.

Major AI-IoT Application Areas in Renewable Energy Systems

p0.24 p0.25 p0.23 Application	**IoT contribution**	**AI contribution**	**Expected operational value**
Solar/wind forecasting	Weather, irradiance, wind, inverter, and turbine telemetry	Time-series prediction, probabilistic forecasting, hybrid physical-data models	Better dispatch, lower reserve needs, reduced curtailment
Predictive maintenance	Vibration, thermal, acoustic, electrical, and fault logs	Anomaly detection, classification, remaining useful life estimation	Lower downtime, targeted maintenance, improved asset availability
Microgrid control	Local metering, inverter status, storage state, switch status	Optimization, RL, load and generation prediction	Stable islanding, efficient storage use, resilient local operation
EV charging	Charger status, user sessions, battery state, price and grid signals	Scheduling, demand prediction, RL, user-behavior modeling	Lower peak demand, lower charging cost, renewable-aligned charging
Smart homes/buildings	Occupancy, appliance, HVAC, PV, and battery data	Load disaggregation, HVAC optimization, appliance scheduling	Energy savings, comfort-aware demand response
Digital twins	Continuous asset and grid telemetry	Simulation, diagnosis, predictive analytics, scenario testing	Faster planning, safer control validation, lifecycle optimization

Integration Challenges

The data quality and governance provision.Data Quality & Governance

This is because there are fewer reported issues related to data than algorithmic issues, and this implies that data-related issues have a greater impact. Renewable Energy data sets are often plagued with missing data, sensor drift, inconsistencies in time or sample rates, inconsistencies in connection with weather exceptions and changes in geological boundary features without records. Model trained under this conditions can yield good performance on an unseen test set, but fail miserably in the real world. Excessive restrictions on access to operational data – It is often security sensitive or commercially sensitive – is an added challenge for the utilities and R&D community. Then, the need for standards-aligned benchmark datasets is greater for the purposes of everyday use than for publication, and they require rewriting, anonymizing, and curating.

Interoperability and Standardization

Unlike "AI" deployments, the majority of deployments for "AI-IoT" aren't in the context of a single vendor ecosystem. These devices must constantly communicate between each other between the inverter, smart meter, building controller, EV charger, DER energy management platform, SCADA and the energy market interface. The same voltage, current, availability, or state of charge could be known by different names and measurements, use different scales, time-stamp different, and/or could be sampled differently depending on the manufacturer's device. On this side, good guidance – "how to" – can be found in NIST and IEEE standards, with meaningfully missing pieces to be filled in when deploying AI markets into systems older even than the standards themselves.

Cybersecurity and Privacy

Coordinating the system on a system wide level means more attack surface. Denial-of-service attacks on the communication infrastructure, the possibility to operate some of the control system's sectors or plug faked data into the sensor streams to poison the ML models, and insecure communication channels or possibility to control the firmware on field devices are among the potential attacks. NISTIR 7628 specifies a risk-based perspective to the smart grid cybersecurity, but it also offers a reasonable reference [6]. When applying the techniques of AI-IoT, all of these steps must be taken into account at the outset of the design of the AI integrated system, not after the model was trained on test data and measured to see if it performed well.

Explain, validate and bear responsibility for models.

It's important to distinguish between the energy sector, where the model recommendation must be operationally acceptable (thus immune from the back and forth between modeler and operator), despite its average level of accuracy. For switching decisions, generation curtailment, loading shedding and charge limits all require a model, alongside predictions, with uncertainty estimates, and an understanding of what might have influenced the generation output as well as an understanding of what the model did under unusual or unforeseen conditions. To achieve an adequate validation, the use of historical data for back-testing is not enough, it should also be tested on a wide range of simulation scenarios, on HIL systems, on temporary field tests and during the full deployment time by testing with care. The weight of these requirements is increased by liability issues, as automated decisions can have a direct impact on end customers, generators and on the overall grid reliability.

Lack of computing/drinking water resources

Processors, memories and battery consumption are the limitations edge AI devices face in improving communication efficiency and reducing response time. The tuning question is a tuning question that doesn't really fit into the field of renewable energy research: How many joules does it take to run intelligence that is supposed to help make electricity systems more sustainable? These include being able to design at the point of carbon estimation of the deployed AI system, selection of energy-efficient hardware, perform inference only when events occur, quantise and compress model parameters.

The regions of economic and regulatory restrictions.

Technological solutions, such as an AI-IoT system, may have potential but, if not backed by institutional controls, they simply will not turn into a deployment. A way of cost recovery for utilities is required, a uniform and clear market access process for aggregators, customers needing the financial incentives to make participating worth their while and regulators needing audit trail which is both fair and secure for automated decisions. Therefore, the engineering or the algorithm isn't the only issue entering such an AI-IoT system; the market design, the procurement structure that will withstand regulatory and accountancy scrutiny becomes a problem.

Integration Challenges and Recommended Research Responses

p0.32 p0.36 Challenge	Practical effect	Recommended response
Poor data quality	Inaccurate forecasts and unreliable anomaly detection	Data validation pipelines, sensor calibration, metadata standards, benchmark datasets
Interoperability gaps	Vendor lock-in and costly integration	Standards-aware data models, semantic

		mapping, open interfaces, conformance testing
Cybersecurity threats	Manipulated control actions and privacy leakage	Secure device identity, encryption, intrusion detection, adversarial testing, zero-trust architecture
Low explainability	Weak operator trust and regulatory resistance	Explainable models, uncertainty reporting, human-in-the-loop review, model cards
Scalability limits	Pilot success but poor field deployment	Edge-cloud partitioning, federated learning, modular architecture, staged pilots
High compute cost	Unsuitable edge deployment and avoidable energy use	Model compression, efficient inference, hardware acceleration, lifecycle energy accounting
Regulatory uncertainty	Slow adoption and unclear liability	Auditable logs, standards alignment, transparent governance, policy sandboxes

Synergistic Effects of AI and IoT

Here, the goal is to promote the use of the core concept (operational closure) of assessing the integration of AI and IoT. When linking IoT, a substantial amount of data can be utilized without the help of AI. Often, algorithm development takes place without talking about data context related to IoT and the algorithms are based on out-of-date, incomplete and missing data. The more inconsequentially the elements of sensing, inference, control and confirmation are tied to each other, rather than being separated from each other, the more the combination is innovative.

The first one is closed loop operation. In case the PV plant includes irradiance sensors and an inverter monitoring system it can forecast the PV plant performance, identify the bad inverter strings and send the data directly to the inverter adjustment programmes and/or maintenance programmes. A micro grid can have the following intelligence about what loads it's powering and what renewable resources are, as they are coming online, and can then request additional storage if it requires them and update that as the load evolves. In all application domains analysed in this review, this pattern is used in all data acquirance types with direct consequence as part of operations that can lead to following up action, when… This can be utilized at any potential point where operations can benefit as a result, such as coinciding with the benefits of getting data nearer to following up action or other ways.

This is an anticipatory or not a reactive effect is the 2nd effect. The insight into the typical conditions that may occur before these issues will arise enable you to take action in advance before a problem is realised, with the conventional alarm system triggered only by the voltage drop or a component problem having occurred. This feature would be most useful in the case of high penetration of DERs and small margins at which these devices operate, necessitating a large number of devices to be coordinated.

The third one is increased visibility of distributed flexibility. When they are not already on the grid, electric vehicles, battery systems, flexible industrial load, smart home, and producers can't play a meaningful role in the grid. This is one example of the flexibility that can be observed, predicted and dispatched individually via AI-IoT infrastructure, which is only possible through manual efforts. The potential benefits – in terms of being able to reduce curtailment, avoid network reinforcement, or utilise renewable generation better – also mean that there is a potential for real tangible outcomes as long as protecting users' privacy and personal preferences is not a will of the warden constraint when it comes to unlocking that flexibility.

Future Research Directions

The Artificial Intelligence – Internet of Things (AI-IoT) – Smart System Design Awareness (SWK-OSD-2023-IA) event has come to a close.The Artificial Intelligence – Internet of Things (AI-IoT) – Smart System Design Awareness (SWK-OSD-2023-IA) event is over.

Reference architectures with intentional connection of AI functions with existing smart grid standards, DER interconnection and communication standards need to be further researched. The architectures should answer some of these basic questions which are not yet reported in research: Where is the model trained vs. Where is the inference? Do the names of the data variables and explanations remain the same throughout the components? How and what should be logged in this automated decision if there is an operator judgment that opposes the model's decision, and who should have the final say in these conflicting decisions for audit purposes?

Lifting of Jury Duties (Open Benchmark Datasets and Reproducible Evaluation).

There is not equity in assessment criteria. There are huge variations in data, pre-processing, forecast interval, metric, etc. between studies and it is difficult to compare results with published studies. Publicly available benchmarks, with the ability to capture PV generation, wind generation, EV charging demand, EV residential load profile, inverter fault signatures and scenarios for microgrid controlled scenarios are highly desired and will significantly aid in the repeatability of evaluation of performance. Also the abnormal operating events should be included in the data recorded as well as the data recorded as missing and the realistic time varying distribution of the events, because data are not, in practice, recorded under optimum operating conditions.

Defend unauthorized use of Edge AI & Federated Learning!

If you can't rely on the centralised data processing due to privacy policy or "latency" requirements, Edge AI and federated learning may come in a handy right-fit solution, but will still not be easy to use. Extensive modelling of the distributed model behavior in the case of failure leading to safety consequences, efficient training in highly non-identical data at different sites, in-depth knowledge of how to secure the aggregation of the models, resistance to model poisoning attacks, communication efficient update mechanisms remain to be performed [16].

Physics-Informed and Constraint-Aware Learning

For any action that the model is touching, it should be included within the AI asset. Some of the performance restrictions that need to be reflected in the forecasts and controls across the power network are operation of the inverter, rate of charge and discharge of the storage, the speed of variations of incomes in/from the inverter, and need to have protection systems. These constraints contribute to learning frameworks that will reduce the risk of running out-feasible suggestions and enhance model predictions in an engineer / operator's mind, with increased confidence.

Digital Twin Validation and Human Oversight

The key to improving beliefs in the "digital twin" is to ensure that it is as accurate as possible, so it can help in decision-making.The more accurate the "digital twin" is, the more useful and trusted actors can be for decisions following the operation. During future investigations, it is also crucial to identify useful and measurable indicators of how good the fidelity of the twins is in terms to how well they are achieving the objective; to develop principled procedures to test the fidelity of the twin to measure the variation in the twin when the field changes; and to have a process for the operator to review, question, approve, and delete the AI-recommended changes to the field before they are applied to the actual environment. The twin not a ‘true’ and ‘true' copy of the actual system whose output would be taken for granted; it is intended to be used as a decision-support aid.

To create sustainable AI-IoT Systems along their life-cycle.To develop sustainable AI-IoT Systems for their life-cycle.

The contribution of the integration of AI with IoT to the environment should be evaluated throughout the system's life cycle — the “whole-life” view; energy saving is only a part of it, and it cannot be predicted, calculated or added up from energy saving alone. Each of these sensors, the communication, data centre, edge computing, and model training processes, and ongoing inference workloads, has its own set of energy and material costs. In addition to the figures highlighted above which are most commonly quoted for the precision and costs reduction, a number of issues should be discussed in the context of any sustainability claims; these include computational overhead, service life of the hardware, life cycle carbon implications etc.

Conclusion

Yes, AI and IoT can provide several operational benefits with the renewables; in fact it will allow for a 'real-time link' to create a relationship between those distributed physical resources and decision-making based on data. The forewarning function, closed-loop control and optimisation come from AI and are supported by the IoT infrastructure as the measurements and communication routes. For all examples discussed in this literature, the successful implementations were those where this linkage takes place not only within the system, but can be proved and demonstrated end-to-end: renewable output forecasting, condition based maintenance, microgrid coordination/operation, EV charging management and demand response and asset lifecycle management assisted by digital-twins.

The first line of caution in this review is that, by itself, good performance of the algorithm is not sufficient. If any of the underlying sensors are not reliable, the Recommendation, communicated down through the communication stack to the Operator who will be taking it, does not provide reasons for the Recommendation, or if the Control Action, generated from the Recommendation, is not able to be traced back after the Deployment to an Audited Record, then the compelling result which is projected in the controlled study will not materialise in the operational deployment. There is a need to move forward in the field with a step towards deployable systems that will facilitate standards-based communication and norms for privacy and learning environments, secure edge inference, physics-informed learning and clear human accountability throughout the decision chain, on the grids where renewable generation is all pervasive.

Author Declarations

Before submitting this section, modify formatting and provide disclosures as applicable to paper to be submitted to a journal of meeting submission following journal guidelines. The statement of indorsement will contain information on the funding source(s), conflict of interest disclosure by the authors, availability of underlying data and indication of the contributions of the authors provided by most journals. Depending on the nature of the research an ethics statement may be required. The use of the AI writing (or editing) tools in preparing the manuscript is to be reported here if the Journal makes requirements about the use of such tools.

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