Volume 2 Issue 3, 2026

DOI: https://doi.org

International Journal of Advanced and Innovative Research
Journal homepage :https://scholarclub.org/index.php/IJAIR/login

Machine Learning-Based Solar Energy Forecasting Using Environmental and Weather Data for Smart Renewable Energy Systems

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ARTICLE INFO:

Received:
05 06 2026
Revised:
25 07 2026
Accepted:
25 08 2026

Keywords:
Machine Learning; Solar Energy Forecasting; Photovoltaic Systems; Weather Data; Environmental Data; Renewable Energy; Smart Energy Systems.

ABSTRACT

With the increasing deployment of solar photovoltaic (PV) technologies, accurate solar-energy forecasting for smart and flexible renewable-energy systems has become more crucial. But solar energy generation is subject to significant variations depending upon the environment and atmosphere as well as time and place, and precise forecasting is particularly difficult because of these factors. Uncertainties associated with solar PV generation, due to variability in solar irradiance, cloudiness, temperature, humidity, wind speed and precipitation, as well as seasonal and time-dependent weather variability, can significantly affect PV generation and uncertainty for energy planning and grid operation. In this context, the current research investigates the potential of machine-learning (ML) techniques in the context of solar-energy forecasting and its contribution to smart renewable-energy management, using environmental and weather data. The study uses qualitative research, interpretivist, and exploratory research design using documentary and secondary sources. It critically synthesizes research articles from peer-reviewed journals, critical reviews, studies on renewable energy, meteorological publications, technical documents and authoritative institutional sources. The thematic synthesis reveals five interrelated findings: environmental and weather parameters are essential input factors for understanding solar energy generation variability; ML techniques offer flexible tools to uncover complex relationships in meteorological and energy-related data; data quality, availability, temporal resolution and uncertainty are significant factors affecting the reliability of forecasts; explainability and context-specific model selection are essential to understanding the forecasting process and to support practical decision-making; and the integration of forecasting capabilities with smart renewable energy systems can enhance energy management and operational coordination. The insights suggest possible applications in energy storage scheduling, smart-grid management, grid balancing, distributed generation, and integration with renewable energy. The prospect of using ML for solar forecasting has great promise for enhancing the responsiveness and coordination of renewable energy systems, but its utility will depend on the quality of data used, the uncertainty of the environment, the transparency of models, and how well they can be applied in the context of particular energy systems.

INTRODUCTION

The transition to renewable energy has been strengthened in many parts of the world, leading to the deployment of technologies that help to decrease reliance on fossil fuels and which can contribute to increasingly electrified economies. One of these technologies that is gaining particular importance is solar photovoltaics (PV), which can be scaled up, is becoming increasingly cost competitive, and can be deployed for both centralized and distributed generation. New data suggests that solar PV has become the linchpin in global renewable energy capacity growth, and is projected to continue to be one of the primary growth drivers for renewables electricity generation until the end of the decade (International Energy Agency [IEA], 2024). On the other hand, the growing number of distributed and utility scale PV installations also presents new PV operational challenges, since electricity production from PV resources is intrinsically dependent on the changing environmental conditions. As a result, there is an urgent need for forecasting methods that are able to capture and react to variability in generation to better integrate solar power in these systems.

Solar-energy forecasting is thus becoming an integral part of the energy-system planning and operation. Accurate predictions can assist in electricity scheduling, the management of energy storage, grid balancing, demand management, microgrid operation, and the management of distributed energy resources. The greater the amount of solar power, the more uncertainty there is in PV output, which can impact the relationship between supply and demand of electricity and make decisions around dispatch and storage more complex. The existing literature highlights that PV electricity intermittency is a key challenge that hinders its integration into the electricity market (Gaboitaolelwe et al., 2023; Yang et al., 2022). Forecasting is especially relevant for smart RES systems because the information on the production expected from a RES can be used to make more responsive decisions on energy management than to consider solar production as an unpredictable energy source.

The main challenge is solar generation is highly dependent on environmental and meteorological variations. The solar irradiance becomes a fundamental factor to the PV's output, and cloud cover may cause immediate and short-term variations. The availability of solar energy and PV-system performance may also be effected by other factors such as temperature, humidity, wind, precipitation, geographic location, seasonality and time of day. They are not independent variables and can give rise to nonlinear, place-dependent patterns when they interact. Meteorological conditions, forecasting time, geographical location, and input features are thus important factors influencing PV forecasting approaches, according to research (Gaboitaolelwe et al., 2023; Tian et al., 2023). Such abrupt changes are especially strong if the clouds are moving quickly, or the atmosphere conditions are varying, so that they are hard to capture using the streamlined assumptions.

The traditional forecasting methods have been based on physical models, statistical time series methods or numerical weather information. As physical approaches can help to provide useful representations of solar-resource behavior, statistical approaches can help to identify temporal patterns in historical observations. However, at various weather stations and time scales, complex atmospheric relationships and interactions may make the use of any one of the traditional methods less suitable. The recently published reviews thus focus on physical, statistical, machine-learning, deep-learning, ensemble and hybrid methods and the ongoing quest for forecasting methods that can cope with the various operational settings (Yang et al., 2022; Santos et al., 2024).

An important methodological approach that has developed recently is called machine learning (ML), which is capable of discovering complex relationships between a large and diverse set of data without having to explicitly specify each of the relationships beforehand. Solar-generation pattern can be related to environmental predictors through supervised learning methods, and various prediction structures can be combined through ensemble methods. Non-linearities and temporal relationships can be captured by representing them in the form of neural networks or deep learning architectures, and sequential forecasting problems are especially well suited to the recurrent approach. Hybrid approaches also aim to blend the advantages of data-driven learning with the physical insights gained from existing energy models (Santos et al., 2024). The literature shows a significant variation in the PV forecasting using ML methods, in terms of algorithm used, input variables, forecasting durations, climate conditions, and PV system locations (Gaboitaolelwe et al., 2023).

But, the usefulness of ML forecasting is critically linked to the quality and nature of the environmental and weather data. Meteorological data can be incomplete, noisy, with varying temporal resolutions, with errors in measurements or with spatial gaps. The variability between weather stations, satellite observations, remote-sensing data and local PV measurements also can impact the representation of environmental conditions. Furthermore, uncertainty in the atmosphere implies that forecasting shouldn't be viewed as merely a technical task of choosing the most advanced algorithm. Contextual factors, the characteristics of the data, forecasting horizon, generalization, and fair comparison of the approaches are increasingly highlighted in reviews (Tian et al., 2023; Santos et al., 2024). The demand for forecasts that are useful at locations that are widely distributed, in addition to the development challenges presented by the growing remote sensing and distributed PV technologies, further emphasizes the importance of developing forecasts that are useful at locations that are spatially distributed (Zhang et al., 2024).

When forecasting is linked to smart renewable-energy systems, these issues are of increasing significance. Forecast information can help with battery-storage scheduling, microgrid coordination, demand response, distributed generation, energy-management systems and grid balancing. However, moving from research to a real-world smart-energy application is not easy. The value of an approach may vary depending on geographical context, forecasting time horizon, data availability, model complexity, computational requirements, interpretability and changing environmental patterns. Recent work on hybrid forecasting also indicates that hybridisation of physical knowledge and data-driven tools could be useful to deal with nonlinearities, enhance generalization and highlight the importance of making meaningful methodological comparison (Santos et al., 2024).

While significant research efforts have been dedicated to solar forecasting using ML, there is a key conceptual shortfall. Current studies often focus on comparing algorithms or predicting the performance of these algorithms, but the relationship between the environmental and weather information, uncertainties, algorithm selection, interpretability and smart-energy applications is not consistently integrated within a single analysis. The challenge is not just identifying which ML technique is better, but understanding how environmental information is interpreted, what limitations can be derived from the quality and uncertainty of this information, and how forecasting can be meaningfully integrated into the more distributed and intelligent energy systems. This gap offers justification for qualitative synthesis beyond a comparison between the technical models, to build a coherent picture of the role of ML-based forecasting in the smart renewable-energy systems.

This study is intended to investigate the application of machine learning to environmental and weather data to predict solar energy and the potential of solar-energy forecasting to aid in smart management of renewable energy. The study takes a qualitative, interpretivist and exploratory documentary approach that synthesises existing scholarly and authoritative evidence, but not a new ML experiment. It provides answers to four questions: (1) How is the representation of environmental and meteorological variables in ML-based solar-energy forecasting research? (2) What are some implications of the literature in terms of data quality, uncertainty, forecasting horizons, and geographical variability? The practical relevance of ML based forecasting is discussed in terms of (3) model selection, explainability and hybrid approaches, and (4) how solar forecasting can be used to support smart grids, energy storage and microgrids, and wider integration of renewables.

Theoretically, the study brings together the different discussions on environmental variability, ML forecasting, uncertainty, and smart-energy applications to offer an integrated interpretive perspective. In practice, it indicates what factors to consider when applying forecast information in increasingly decentralised renewable-energy systems, of relevance to energy planners, system operators, researchers, and technology developers. The study thus does not view ML as a panacea for dealing with solar variability, but rather as a potentially useful tool for decision making support that is conditioned on the quality of the data, contextual appropriateness, transparency and integration of the system.

LITERATURE REVIEW

In response to the widespread installation of PV systems and the increasing need of integrating VREs into increasingly flexible electricity networks, the literature on solar-energy forecasting has grown. There has been a recent shift in scholarship from traditional physical and statistical predictions to machine-learning (ML), deep-learning, ensemble, and hybrid methods. However, there is a lack of uniformity in the literature with respect to the forecasting techniques, environmental variables, uncertainty and energy-system applications. However, there is a need for a critical synthesis that considers not only the capabilities of ML methods but also the quality of environmental information, contextual differences, the explainability of the methods, and how they can be practically integrated into smart renewable-energy systems.

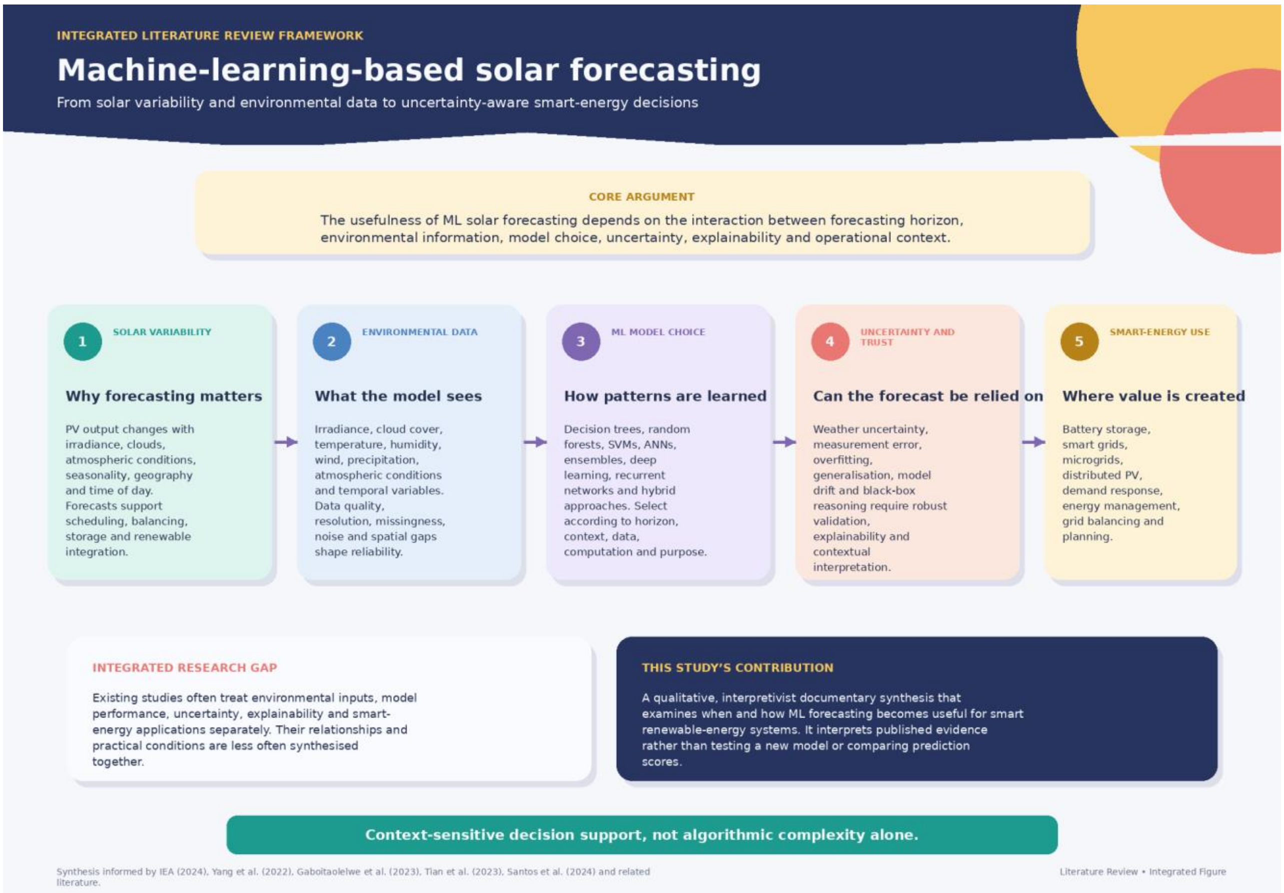


Figure 1. Integrated literature-review framework for machine-learning-based solar forecasting.

The use of solar energy is highly dependent on its availability and predictability

Because PV output varies with factors such as irradiance, clouds, atmospheric conditions, seasonality, geographical location and the time of day, solar-energy generation is inherently variable. The literature generally indicates that this variation leads to operational issues for electricity systems of growing PV penetration. Forecasting is therefore considered as a vital tool for enhancing scheduling, balancing, storage coordination, and renewable energy integration (IEA, 2024; Yang et al., 2022).

A key difference in the literature is that related to forecasting horizons. Very-short-term forecasting is related to rapidly changing cloud conditions and operation decisions on the grid while day-ahead and longer-horizon forecasting are more relevant to scheduling, market participation and planning decisions. Thus, there is no single forecasting method that is suitable for all forecasts. According to reviews, the prediction accuracy and the suitability of the methods greatly rely on the time horizon, climatic conditions, data availability, and PV system characteristics (Gaboitaolelwe et al., 2023; Tian et al., 2023).

While it is accepted that forecasting is important, the literature on the methods of forecasting sometimes undervalues the meaning of forecasts operationally and focusses more on the improvement of the algorithms. A highly developed forecasting method may not be more useful, if the data it uses is not reliable, the forecast is hard to understand, and the computations are not practical for real-time use. This indicates that solar forecasting must be considered as a decision support problem that is dependent on the particular context in which it is being used, and not just a model selection process.

During this theme, various aspects of environmental and weather data for solar-energy forecasting will be discussed

Many solar-forecasting methods are based on environmental and meteorological data. Solar irradiance is key because it is directly linked to the solar resource available for PV systems. Research also suggests that other factors, such as cloud cover, temperature, humidity, wind speed, precipitation, atmospheric conditions, seasonality, and temporal variables, could play a role in explaining this phenomenon (Gaboitaolelwe et al., 2023; Yang et al., 2022).

The literature suggests that these variables have different values, depending on their temporal and spatial resolution. Short time scale observations may better capture fast changes related to clouds, while longer time scale observations may capture the seasonal patterns. However, higher data resolution does not necessarily equal improved forecasting since meteorological observations may be missing, noisy, be inconsistent, or have spatial gaps. Local weather observations, satellite information and numerical weather products can also differ, which can affect the representation of atmospheric conditions.

This is an important tension to consider in ML based forecasting. Data-rich methods may be able to represent and model complex relationships, but they can also be sensitive to data quality and input selection. Recent reviews thus highlight that the forecasting performance needs to be understood considering its data characteristics and not only due to algorithm sophistication (Tian et al., 2023; Santos et al., 2024). One of the challenges of environmental uncertainty is that atmospheric conditions may vary quickly and historical data may not adequately reflect the current environment. Therefore, the literature provides a general conception of forecasting which involves data availability, reliability, resolution and uncertainty as basic methodological concerns.

The aim of the theme is to apply Machine Learning techniques to solar forecasting

A great methodological variety is seen in the literature of solar forecasting based on ML. The traditional ML methods such as decision-tree methods, random forests, and support-vector methods are still relevant due to the fact that they are able to model nonlinear relationships without requiring the extensive architecture complexity of deep learning. ANNs provide the flexibility to represent complex relationships and ensemble approaches increase the robustness by building multiple learning structures. With this regard, deep-learning and recurrent architectures have been gaining a lot of interest due to their capability to capture nonlinear and sequential patterns, especially when large temporal data is available (Yang et al., 2022; Santos et al., 2024).

There is not, however, an obvious justification in the literature that more complex models are necessarily better. The computational resources and larger, well-structured datasets may be significant for more complex neural and deep-learning architectures. The black-box nature of their properties can also pose some problems for the user if they want to know how and why specific forecasting patterns develop. On the other hand, simpler models can be more easily explained and used, but may not be as flexible in the case of non-linear environmental relationships.

The combination of the physical knowledge, statistical structures, and data-driven learning is an important attempt to reconcile this tension, and those approaches are known as hybrid approaches. What they have to offer conceptually is the ability to combine different kinds of information, not sticking to one methodological paradigm. However, hybrid systems can also come with additional complexity and adaptations to context may be necessary. Collectively, the above evidence indicates that the selection of a model should be determined by the forecasting horizon, the environment in which the model is being used, data availability, computational needs, the interpretability of the model, and the purpose of the model, and not by the assumption that the newest or most complex ML architecture is superior.

Forecasting Uncertainty, Explainability, Reliability, and Generalization

One of the biggest unsolved problems of solar forecasting is uncertainty. It comes not only from the ML models, but also from inaccurate weather observations, fast-changing weather, missing data, measurement inaccuracies, and varying operating conditions between training and deployment. Thus, a forecasting system may experience conditions that are significantly different from what is in its historical evidence base.

Overfitting and generalization are also mentioned in the literature. Relationships between PV output and the geo-climatic variables are dependent on the geographic location, and a model developed at one site cannot be easily applied to another. Such relationships can vary with the seasons. Another issue is model drift as environmental patterns, technologies and operating conditions can evolve over time.

Explainability is another major issue. Deep-learning and other complex architectures can detect complex patterns, but it may be challenging to understand the decision-making process within the architecture. However, for operators of an energy system, knowing what factors affect a forecast may be important when considering reliability and for making energy system operational decisions. In recent years, the scholarship more and more focuses on transparency, robustness, contextual validation and meaningful interpretation, rather than considering forecasting as simply a predictive activity (Santos et al., 2024).

The problems highlight a major weakness in the current literature: The application of the actual model and its performance, environmental inputs, uncertainty, and practical reliability are dealt with in isolation. A more comprehensive view of these factors in relation to each other and their role in the usefulness of a forecasting system in various contexts is required.

Solar Forecasting for Smart Renewable-Energy Systems

Solar forecasting is not only relevant for forecasting PV output, but also for the practical application. Forecast information can help with managing the battery storage, coordinating the smart grid, coordinating microgrid operations, demand response, planning distributed generations, and other energy-management services. For a more decentralized electricity systems, forecasting can supply information which is necessary to coordinate multiple distributed renewable resources and flexible technologies.

The relationship is widely recognised in the literature, but the link between forecasting research and smart-energy applications is not well established. Most studies focus on forecasting methods, but relatively little attention is paid to the process of making forecasts into operational decisions. The relevance of forecast uncertainty in this context is particularly highlighted by the storage scheduling, grid balancing and demand-response decisions which could rely on the reliability and timeliness of forecast information.

Smart renewable-energy systems thus need more than sophisticated forecasting models. They need the forecasting methods that are reliable enough, easily interpretable, adaptable, computation efficient and suitable for the operations of energy-management systems. This serves to emphasize the importance of considering the context of ML forecasting in the broader environment and energy system.

Integrated Research Gap

The literature reviewed shows promising developments in solar forecasting using ML, but there is fragmentation in five interrelated segments: solar variability, environmental data, ML methods, uncertainty and explainability, and smart-energy applications. Current studies have shown the importance of meteorological information, and the potential of data-driven methods, but most work has dealt with them individually. Data quality and geographical context could be ignored in the algorithmic comparisons and environmental studies might not pay enough attention to model interpretability and operational integration. Likewise, forecasting research is not always able to elucidate the impact of uncertainty on practical applications like storage, microgrids and grid balancing.

This study is an exploratory synthesis of documentary and secondary data, using a qualitative interpretivist approach to fill this gap. It does not test a new ML model or compare the prediction score of different models, but rather it explores how the existing research framed the relationship between environmental and weather data, ML-based forecasting, uncertainty and smart renewable energy management. This integrated viewpoint is crucial for not only realizing if ML can contribute to the solar forecasting, but also when and how solar forecasting can be of value to smart renewable-energy systems.

RESEARCH METHODOLOGY

Research Philosophy

The interpretivist research philosophy is adopted because this study is based on knowledge, meanings and relationships built in the existing literature. Instead of looking at solar-energy forecasting as a phenomenon that is measurable in an objective manner and that needs to be predicted via new experimental approach in the field of renewable energy forecasting, the study aims at understanding the way in which previous research has conceptualized the notion of machine learning (ML), environmental and weather variables, uncertainty, forecasting reliability, and smart renewable-energy integration. The interpretivist approach provides the researchers the opportunity to critically analyze multiple viewpoints and contexts meanings found in divergent sources instead of taking for granted that one method of forecasting is always better (Creswell & Poth, 2018).

Research Approach and Design

The study used the qualitative exploratory and documentary research design using secondary data. It aims at developing an interpretive grasp of what is known about ML based solar forecasting, and not to create new solar forecasts. Documentary research is especially well suited because vast knowledge regarding PV forecasting, meteorological variables, ML methodologies, uncertainty, as well as smart energy systems can be found in scholarly and institutional publications. The exploratory orientation allows the study to uncover common themes, tensions, and constraints in the methodology as well as relationships that may not be fully identified using a quantitative only comparison of forecasting models.

Importantly, this study does not run a new experiment of the ML or produce new datasets, forecasts, prediction scores, statistical tests, or model-performance results. On the other hand, the documents that have been published before will form the documentary material for the qualitative interpretation.

Sources of Evidence

Authentic and publicly available documentary sources form the basis of the evidence and include peer-reviewed journal articles, scholarly review papers, conference literature that is relevant to the subject, research on renewables, publications by meteorological institutions, technical reports, institutional publications, and authoritative literature from energy sector institutions. Recent literature from 2020 to 2026 has been preferred due to the rapid advancements in ML, renewable energy technologies, weather data systems, smart-grid applications etc. Where earlier methodological or conceptual sources are retained, they are those that provide foundational concepts which are still applicable.

The evidence is restricted to literature that explicitly deals with the fields of solar-energy forecasting, PV systems, environmental/meteorological aspects, ML/Deep Learning techniques, forecasting uncertainty, explainability, hybrid methods and smart renewable-energy applications.

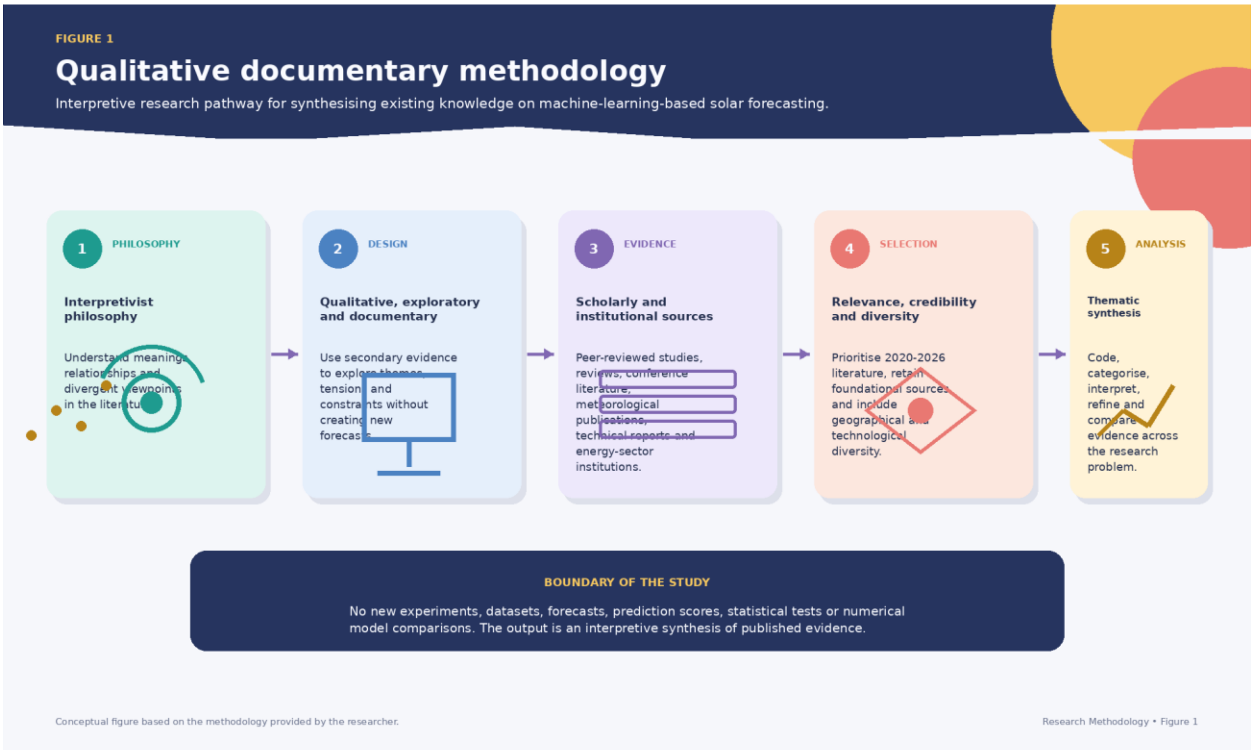
Source Selection Criteria

Sources are chosen based on their relevance, scholarly nature, methodological soundness, timeliness, and close connection to the research goals. Solar forecasting papers that include substantive discussion of the environmental, computational, or energy-system aspects of solar forecasting, and are peer reviewed and authoritative, are preferred. Sources are rejected if they do not have scholarly credibility, are not relevant to the research questions, or make unsupported claims. Special attention is also paid to geographical and technological diversity to prevent the synthesis being perceived as the solar forecasting process being context independent.

Data Collection and Documentary Organization

Documentary evidence was systematically identified by searching related scholarly and institutional literature on combinations of concepts including machine learning, solar forecasting, PV prediction, weather data, environmental variables, solar irradiance, forecasting uncertainty, explainable AI, hybrid forecasting, smart grids, energy storage, and renewable-energy integration. The relevant sources were examined to identify those that are conceptually and methodologically relevant and then arranged in a manner relevant to the research questions.

The study conceptually gathered information related to forecasting inputs, forecasting model learning techniques, environmental factors, data constraints, uncertainty, interpretability, methodological choices, and applications to smart energy systems, rather than using numerical metrics for comparison.



DATA ANALYSIS

Qualitative thematic analysis based on systematic coding, categorization, interpretation, and thematic refining (Braun & Clarke, 2006, 2021) was used to analyze the documentary material. The analysis started with familiarisation with literature selected, the identification of concepts and arguments that recurred, and coding. These codes were then categorized into larger categories of concepts. Themes were restated and elaborated, with the aim of capturing the essence of patterns in the documentary evidence, not just individual instances.

The analysis revealed 5 main themes:

Environmental and Weather Variables — looking at the variables of irradiance, cloud cover, temperature, humidity, wind, precipitation, atmospheric conditions, seasonality and temporal variables.

Machine Learning Approaches — old school ML, neural networks, ensemble methods, deep learning, recurrent and hybrid approaches.

Data Quality, Uncertainty, and Reliability — missingness, noise, resolution, uncertainty of weather, generalization, forecasting reliability.

Explainability, Hybrid Approaches, and Model Selection — discussing the transparency of models, computational complexity, contextual appropriateness, and combining physical and data-driven models.

Smart Renewable-Energy Integration — exploring forecasting applications in smart grid, energy storage, microgrid, distributed PV, energy management and grid balancing.

The last synthesis compares and contrasts elements that are similar and different among the literature and analyzes the implications for the research problem.

Trustworthiness

Credibility, dependability, confirmability, and transparency are used to enhance trustworthiness. Multiple use of scholarly and authoritative evidence enhances credibility. Documentary triangulation permits the findings to be viewed across peer-reviewed research, reviews, technical publications and institutional sources, not relying upon one type of evidence. Consistent source-selection and thematic-analysis procedures help to ensure dependability and confirmability is achieved through interpretation based on published evidence instead of personal assumptions. Consistency is further enhanced by the fact that the analytical process is clearly and transparently documented and makes it possible for the reader to understand the development of the five themes.

Ethical Considerations

Since the study is based on published documents, ethical issues include proper citation, intellectual integrity, responsible interpretation and preventing plagiarism. Sources are accurately quoted, statements are not exaggerated and evidence is not fabricated or manipulated. The study does not fabricate information about participants, information sources, interviews, experiments, or numbers. People's ideas are credited appropriately using APA 7th edition citation practices.

Methodological Limitations

There are some limitations in the methodology. Relying on the published literature will introduce the effect of availability of publications and publication bias. Additionally, previous studies vary significantly in geographical context, forecasting period, PV technologies, environmental conditions, data sources and methodological approaches, making it difficult to compare the studies conceptually. In addition, the complexity of individual forecasting environments can't be perfectly captured with documented evidence. Lastly, this is an interpretive and qualitative study, and thus, it is not possible to test the effectiveness of the ML in forecasting performance in an experimental manner or compare the algorithms numerically. These constraints are consistent with the aim of the study which was to interpret, rather than to create a new predictive model.

FINDINGS and DISCUSSION

Five interconnected themes emerged from the thematic synthesis of documentary evidence that will help explain how machine learning (ML) can aid solar-energy forecasting and smart renewables systems. The results provide insights to how forecasting can be useful, rather than simply a computation problem, and show that the utility of forecasting is dependent on the interaction between environmental variability, weather data, data quality, the design of the ML, uncertainty, interpretability, and the requirements of the energy system. The themes also illustrate that there is no single type of forecasting that can be deemed as universally applicable for geographical, temporal and operational contexts.

Theme 1, students will explore how environmental and weather factors serve as the foundation for solar forecasting

Thematic finding. The evidence is overwhelming that the bottom-line of solar-energy forecasting is the environment and meteorological conditions. PV generation is directly proportional to solar irradiance and cloud cover can result in fast changes in the amount of solar radiance available. The impact of weather conditions on PV output is further affected by other factors such as temperature, humidity, wind speed, precipitation, weather conditions, seasonality, geographical characteristics and time of day (Gaboitaolelwe et al., 2023; Yang et al., 2022).

The ability to interpret and compare critically. There is consensus in the literature that the inclusion of weather information is beneficial for the representation of solar variability, but the significance of the components varies as a function of location, climate, forecast range and the resolution of the data. While some variables, such as cloud, can be more significant at shorter time scales, others, like seasonal and temporal variables, can be more important at longer time scales. This contextual dependence is problematic because one might expect a set of environmental predictors to be universal and optimal.

The results also show that environmental variability is not a problem of increased number of variables. The atmospheric interactions are complicated and the potentially fast change in weather can give rise to uncertainty that cannot be fully represented by historical data. Therefore, environmental information needs to be interpreted as a resource along with an uncertainty. This interpretation relates directly to the first research question that focuses on the representation of environmental variables in ML-based solar forecasting.

Significance and implications. In order to have environmentally appropriate inputs, and enough temporal and spatial resolution forecasting systems are required. These relationships are significant for smart energy systems, because it is important to have correct information about changing weather in order to make further decisions regarding storage, balancing the network and managing energy.

Theme 2: Machine Learning for capturing complex solar–weather relationships

Thematic finding. The literature shows that ML is a flexible representation option for the relationship between environmental conditions and PV generation that is nonlinear. Research in solar forecasting has investigated a variety of traditional ML models, tree-based models, support-vector models, neural networks, ensemble learning, deep learning, recurrent models, and hybrid models (Tian et al., 2023; Santos et al., 2024).

Interpretation and critical comparison. The evidence is not indicative of a straightforward progression of when new and/or more complex algorithms have been consistently found to be better. While conventional ML methods can be more practical due to their relatively simple implementation and interpretation, they can also have their limitations in terms of performance. The learning structures can be used in combination with ensemble approaches and neural and deep learning methods can represent very complex relations and temporal dependencies. Recurrent architectures are of particular interest in situations where there are sequential weather and generation patterns.

But the added complexity can be associated with more computational needs, data needs, and interpretational challenges. Physical knowledge and data-driven learning are being meshed together in hybrid approaches that seek to overcome some of these limitations. Their importance is that they show that solar forecasting is a combination of physical processes and patterns. However, there may be more methodological problems with hybrid systems.

These are all signs that model selection should be contextual and not algorithmic. The choice of a method should depend on forecasting horizon, availability of data, climatic environment, computational resources, and the purpose of the operation. This discovery supports the second research question of the study which is about the role and limitations of various ML techniques.

Practical implications. Thus, energy-system developers should not expect the most sophisticated energy system to deliver the most useful operational information. On the contrary, ML has to be chosen based on the nature of the forecasting problem and the needs of the system where forecasts are to be applied.

Theme 3: Data Quality, Uncertainty, and Forecasting Reliability.

Thematic finding. It was found that data quality was a key factor in the quality of the forecasts. Important challenges highlighted in the literature include missing observations, measurement errors, noise, temporal variability in observations, limited spatial observations, and uncertainty in weather information (Gaboitaolelwe et al., 2023; Tian et al., 2023).

Interpretation and critical comparison. This discovery defies the technology-driven notion of ML forecasting. A sophisticated algorithm cannot eliminate weaknesses originating from poor-quality inputs. The selected weather sources can match weather conditions at a different spatial and temporal scale, and weather conditions at the local PV system may not well be reflected in the broader weather observations. But generalization is made more complicated by geographic variations, because what that climate one learns may not be directly applicable to another.

Overfitting and model drift are also identified as risks with the evidence. Relationships in the past may differ, depending on changing environmental conditions, PV technologies, and/or operational circumstances. Thus, what is suitable in one kind of documentation may not be suitable in another and the same in another.

This theme is especially relevant given that uncertainty in the forecast comes from several sources, namely: model uncertainty, data uncertainty, and weather uncertainty. This is not a complete answer to the problem of uncertainty as it can only be treated as an ML problem. The findings directly answer the third research question by showing that reliability of forecasts is influenced by the interplay between the characteristics of the data and the methodological design.

Practical implications. More focus needs to be paid to the data validation, appropriate temporal resolution, missing-data management, contextual interpretation and continuous assessment of model relevance. For smart grids and storage systems, the uncertainty in the forecast is vital as decisions for their operation could rely on imperfect information.

Theme 4 Explainability, Hybrid Intelligence, and Context-Sensitive Model Selection

Thematic finding the 4th theme is about the balance between sophistication of prediction and interpretability. Non-linear relationships can be effectively captured by complex ML and deep-learning models, however, practitioners may find it challenging to comprehend the decision making process of such models. This raises issues of transparency and confidence for forecasting information (Santos et al., 2024).

Interpretation and critical comparison. For energy systems, explainability plays a special role as forecasts are not a goal but are used to guide operations. It is important for the user to have some idea of which environmental factors affect a forecast so that he or she can determine if the results are likely to hold true in the event that his or her environment changes. Meanwhile, the simpler models can be more easily understood but may not be as effective at capturing highly nonlinear relationships.

One way to address this tension is to use hybrid intelligence. Together with the physical understanding, ML can contribute to a more context-aware forecasting framework, and ensemble strategies can incorporate various sources of predictive information.

Integrated Thematic Findings and Discussion of Machine Learning-Based Solar Energy Forecasting

1. Environmental and Weather Variables Solar irradiance, cloud cover, temperature, humidity, wind speed, precipitation, atmospheric conditions, seasonality, geographical location, and temporal factors strongly influence PV generation. Solar forecasting is fundamentally dependent on changing environmental conditions. The importance of individual variables varies according to climate, location, forecasting horizon, and temporal resolution. Therefore, environmental data are both essential forecasting inputs and major sources of uncertainty. Better representation of weather conditions can support more informed energy scheduling, storage planning, distributed PV management, and grid balancing.

2. Machine Learning for Solar Forecasting ML approaches can identify complex and nonlinear relationships between environmental variables and photovoltaic generation. Conventional ML, ensemble methods, neural networks, deep learning, recurrent models, and hybrid approaches each offer different capabilities. The literature does not support the assumption that the most complex ML model is always the most appropriate. Model suitability depends on data availability, forecasting horizon, computational requirements, environmental context, and operational purpose. Context-sensitive ML selection can improve the usefulness of forecasting information for energy-management systems, microgrids, and smart-grid applications.

3. Data Quality, Uncertainty, and Reliability Missing observations, noisy measurements, inconsistent resolution, measurement errors, weather uncertainty, geographical variation, overfitting, and model drift can affect forecasting reliability. Forecasting limitations cannot be attributed solely to algorithms. The quality and representativeness of environmental data substantially shape what ML systems can learn and how reliably forecasts can be interpreted across different conditions. Data validation, appropriate resolution, uncertainty awareness, and continuous model assessment are important for reliable storage scheduling, grid balancing, and renewable-energy integration.

4. Explainability, Hybrid Intelligence, and Model Selection Complex ML and deep-learning approaches can capture sophisticated relationships but may reduce interpretability. Explainable AI, ensemble strategies, and hybrid physical–ML approaches provide opportunities to combine computational learning with domain knowledge. Forecasting should balance predictive sophistication with transparency and contextual suitability. Greater complexity does not automatically mean greater practical value. Explainability is particularly important when forecasts inform operational energy decisions. Transparent and context-sensitive forecasting can increase confidence among energy managers, grid operators, and other users responsible for energy-system decisions.

5. Solar Forecasting and Smart Renewable-Energy Integration Solar forecasts can support battery storage, smart grids, microgrids, distributed PV, energy-management systems, demand response, grid balancing, and renewable-energy integration. Forecasting has value beyond prediction itself: its importance depends on how forecast information is incorporated into operational decisions. Forecast uncertainty must therefore be considered when linking ML outputs with energy-system flexibility. Reliable forecasting can strengthen coordination between renewable generation, storage, flexible demand, and grid operations, supporting more adaptive and resilient smart-energy systems.

Major Theme	**Key Finding from Documentary Evidence**	**Critical Interpretation**	**Implications for Smart Renewable-Energy Systems**
1. Environmental and Weather Variables	Solar irradiance, cloud cover, temperature, humidity, wind speed, precipitation, atmospheric conditions, seasonality, geographical location, and temporal factors strongly influence PV generation.	Solar forecasting is fundamentally dependent on changing environmental conditions. The importance of individual variables varies according to climate, location, forecasting horizon, and temporal resolution. Therefore, environmental data are both essential forecasting inputs and major sources of uncertainty.	Better representation of weather conditions can support more informed energy scheduling, storage planning, distributed PV management, and grid balancing.
2. Machine	ML approaches can identify	The literature does not support the	Context-sensitive ML

Major Theme	Key Finding from Documentary Evidence	Critical Interpretation	Implications for Smart Renewable-Energy Systems
Learning for Solar Forecasting	complex and nonlinear relationships between environmental variables and photovoltaic generation. Conventional ML, ensemble methods, neural networks, deep learning, recurrent models, and hybrid approaches each offer different capabilities.	assumption that the most complex ML model is always the most appropriate. Model suitability depends on data availability, forecasting horizon, computational requirements, environmental context, and operational purpose.	selection can improve the usefulness of forecasting information for energy-management systems, microgrids, and smart-grid applications.
3. Data Quality, Uncertainty, and Reliability	Missing observations, noisy measurements, inconsistent resolution, measurement errors, weather uncertainty, geographical variation, overfitting, and model drift can affect forecasting reliability.	Forecasting limitations cannot be attributed solely to algorithms. The quality and representativeness of environmental data substantially shape what ML systems can learn and how reliably forecasts can be interpreted across different conditions.	Data validation, appropriate resolution, uncertainty awareness, and continuous model assessment are important for reliable storage scheduling, grid balancing, and renewable-energy integration.
4. Explainability, Hybrid Intelligence, and Model Selection	Complex ML and deep-learning approaches can capture sophisticated relationships but may reduce interpretability. Explainable AI, ensemble strategies, and hybrid physical–ML approaches provide opportunities to combine computational learning with domain knowledge.	Forecasting should balance predictive sophistication with transparency and contextual suitability. Greater complexity does not automatically mean greater practical value. Explainability is particularly important when forecasts inform operational energy decisions.	Transparent and context-sensitive forecasting can increase confidence among energy managers, grid operators, and other users responsible for energy-system decisions.
5. Solar Forecasting and Smart Renewable-Energy Integration	Solar forecasts can support battery storage, smart grids, microgrids, distributed PV, energy-management systems, demand response, grid balancing, and renewable-energy integration.	Forecasting has value beyond prediction itself: its importance depends on how forecast information is incorporated into operational decisions. Forecast uncertainty must therefore be considered when linking ML outputs with energy-system flexibility.	Reliable forecasting can strengthen coordination between renewable generation, storage, flexible demand, and grid operations, supporting more adaptive and resilient smart-energy systems.

Source: Author's thematic synthesis of the reviewed documentary and secondary evidence.

CONCLUSION

The present study covered the emerging significance of the machine learning-based solar-energy forecasting in the era of changing renewable-energy systems which are becoming increasingly variable and decentralized. PV generation is heavily dependent on the environmental and meteorological conditions, such as irradiance, cloud cover, temperature, humidity, wind, precipitation, seasonality and geographical features. The dynamic nature of these conditions can lead to uncertainty and challenge energy planning, storage management, grid balancing, and integration of renewable energy sources. The study therefore investigated the possibility of using machine learning and environmental/weather information together to enhance solar energy management to be more responsive and intelligent.

The research design was qualitatiive, interpretative, exploratory, documentary/secondary-evidence design in methodologically. The study was not a new machine-learning experiment or creation of new data sets or assessment of prediction accuracy; rather, it was a critical synthesis of scholarly and authoritative evidence. The method allowed for an integrated interpretation of the relationships between environmental variability, ML approaches, data quality, smart-energy applications, and uncertainty and explainability.

The thematic findings show that the environment and weather are not just other inputs to forecasting systems, but are part of the forecasting problem. Machine-learning based methods provide flexibility in capturing complex, nonlinear relationships between the environment and PV generation, though they will only be beneficial if the data have good quality, resolution, and are relevant to the problem. This means that complex algorithms are not able to solve uncertainty arising from limited measurements, noise, fast weather changes, geographical variations or variable operating conditions on their own.

Another conclusion is that it is important to strike a balance between complexity and interpretability when forecasting reliability. Data-driven flexibility and domain knowledge can be combined by interpreting the model, using ensemble methods, and hybrid physical–ML methods.Explainable ML, ensemble strategies, and hybrid physical–ML approaches are promising directions to combine data-driven flexibility with domain knowledge. But no single method is considered to be the optimum approach universally. Instead, the model should be selected according to the forecasting horizon, context of the environment, availability of data, computational needs, interpretability, and the purpose of the forecast.

Theoretically, the study is important for its ability to conceptualize solar forecasting as an integrated environmental, computational and energy-system phenomenon as opposed to simply an algorithm-selection problem. This viewpoint links variability in the environment and data quality, ML design, uncertainty management, explainability, and energy usage during operation. In real-world terms, the results are important for renewable-energy planners, for solar developers, for grid operators, for energy managers, for storage managers, for smart-grid designers, and for policy makers who want to better coordinate the variable solar resources.

Smart-energy benefits include battery-storage scheduling, grid balancing, distributed generation, demand management, microgrid coordination, and integration of renewable energy in general, all of which can be aided by reliable forecasting. Forecasting can thus serve as a valuable component of a flexible energy system, if uncertainty and situational constraints of forecasting are recognized.

The study has some limitations, however. The results of its conclusions are dependent on the quality and availability of the literature reviewed and may be an outcome of publication bias and variations in research conditions. Other studies have also had different geographical settings, prediction periods, PV structures, environmental data and methods. As this study is qualitative and documentary in nature, it is not possible to conduct an experiment to validate the performance or superiority of specific ML algorithms.

Future studies should thus build on the qualitative synthesis through empirical testing with multi-location and varied environmental data. The following critical areas of uncertainty-aware forecasting, explainable ML, hybrid physical–ML approaches, transfer learning, real-time forecasting, and integration with smart-grid and energy-storage technologies deserve special attention.

Machine learning has remarkable promise to assist in solar-energy forecasting but sophisticated algorithms are not enough to create reliable smart renewable energy systems. The quality of environmental data, the level of interpretation and understanding of the model selection, uncertainty management, interpretability and effective integration into energy infrastructure must work together. Ultimately, the value of solar forecasting lies in the ability to combine technology with environmental conditions and the need of current renewable energy systems.

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