Weather Impact on DER Long-term Performance: A Formal Verification Approach

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***Abstract*—Distributed energy resources (DERs), such as solar photovoltaic (PV) panels, are essential to modern energy systems, providing resilience and producing clean, local energy. However, their long-term performance is vulnerable to environmental factors, often leading to undetected issues due to the complexity of systematic monitoring. To address this, we propose a work-in-progress approach leveraging stochastic modeling to analyse and verify system requirements. This approach enables a rigorous evaluation of performance under varying weather conditions, as shown in our preliminary results, representing a significant step forward in managing renewable energy resources effectively.**

***Index Terms*—distributed energy resources, solar photovoltaic panels, energy system, quantitative verification**

I. Introduction

Renewable distributed energy resources (DER), such as solar energy systems, are crucial in the global initiative against climate change [1]. However, despite their robustness, these systems are sensitive to various factors that can gradually degrade their long-term performance and eventually compromise energy security [2]. These impacts often remain unnoticed during the system's normal operation, as they are challenging to monitor and quantify systematically.

For instance, weather conditions are well-known factors that significantly influence solar system performance, such as cloudy conditions or rain [3]. Owing to advancements in solar technology, their short-term impact on the stability of power grid is minimal, as a sudden drop in solar panel performance can now be effectively managed by using pre-reserved power (e.g. energy stored in batteries when solar production exceeds demand). Although current systems handle short-term fluctuations well, the long-term impacts of these weather conditions remain less predictable. This unpredictability arises from a variety of uncertain factors and stochastic processes, such as unpredictable rainy days or the sporadic movement of clouds over the solar panels. This inherent stochasticity complicates the assessment of long-term solar panel performance.

In this paper, we focus on applying a well-established formal method, commonly used in analysing stochastic behaviours of computer software, to model and analyse the long-term impact of weather on solar systems; and aim to demonstrate the enhancement of our understanding and predictive capabilities regarding the long-term effects of weather on solar system performance.

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The main contributions of our paper are:

- Modelling the stochastic influence of weather on the long-term performance of DERs using a stochastic model;
- Presenting a formal method for analysing this model, thereby enhancing the predictability and management of long-term impacts;
- Demonstrating the application of this analysis to assess the long-term impact of weather on a simulated solar energy system.

The rest of the paper is structured as follows: Section II reviews related work. Section III discusses the challenges and context motivating our research, emphasising the impact of weather variability on solar PV system reliability and the current methods' limitations. Section IV introduces distributed energy resources and stochastic model checking, with essential terminology for our approach. Section V outlines our method in four concise steps. Section VI demonstrates the method's application and presents preliminary results and Section VII summarises our findings and contributions.

II. Related work

Several existing solutions in the power system domain leverage formal verification methods to ensure system reliability and efficiency. These approaches range from verifying individual components to addressing broader system interactions under varying conditions.

The approaches in [4] and [5] both address the reliability and efficiency of renewable energy systems in different contexts. The former focuses on stand-alone solar PV systems, using formal methods based on model checking to validate the operation of system components like solar panels. While this ensures component reliability, it does not account for weather impacts on energy production or address weather variability. Similarly, the latter discusses the reliability and efficiency of an Energy Router (ER)-based system within the energy internet framework for green cities. It employs Continuous-Time Markov Chains (CTMCs) to model system architecture and Markov Decision Processes (MDPs) to capture electricity trading behaviours, with probabilistic model checking ensuring reliability and communication properties. However, like the former, this approach does not address the resilience of the power system to weather-induced variability, particularly regarding the sensitivity of Distributed Energy Resources (DERs), nor does it consider long-term impacts.

The authors in [6] address system resilience in power grids via formal verification of transactive energy controls. They identify challenges in upgrading traditional distribution systems to support transactive energy and employ TLA+ to formally verify a laminar coordination framework within a Functionally Defined Invariant Architecture. Although this approach effectively uses TLA+ for formal verification of deterministic behaviours, it does not consider stochasticity. Without incorporating probabilistic models, this solution lacks the ability to model and analyse uncertainties such as variable weather conditions affecting DER performance.

The approach in [7] uses formal analysis to compute reachable sets and assess the stability of power networks under deterministic behaviours and various disturbances. However, this method does not account for the stochasticity inherent in real-world power systems, such as the variability in weather conditions that can affect DER performance. Similarly, the research in [8] models the reliability and stability of energy-management systems under adverse weather conditions and varying loads using Timed Automata, verified through the UPPAAL modeling tool. While this framework effectively ensures stability under deterministic conditions, it also falls short by not considering probabilistic behaviours or uncertainties, thereby limiting its ability to fully evaluate the impact of adverse weather on DERs.

In summary, while various formal verification methods have been proposed for different aspects of power systems, our approach stands out by focusing on the stochastic behaviour of DERs under varying weather conditions. Using probabilistic models to dynamically assess system resilience and reliability offers a holistic and adaptable framework for managing uncertainties in power systems reliant on renewable energy. Our approach captures and addresses the uncertainties and long-term effects of adverse weather on DER performance, enhancing overall system reliability and adaptability.

III. Motivating example

Figure 1 shows a simplified representation of solar PV panels installed on the roof of a residential building. This scenario features a single household that relies on solar power to meet its energy requirements. A Battery Energy Storage System (BESS) acts as a critical storage device, capturing excess energy when production exceeds demand and releasing it when the opposite occurs. This system plays a vital role in balancing power flows, enhancing grid stability, and facilitating the integration of renewable energy. When the solar panels and battery cannot meet the power needs, the system connects to the grid to purchase additional energy.

To enable widespread deployment of such systems, they must have minimal impact on grid stability. However, the power generated by solar panels can vary significantly, as

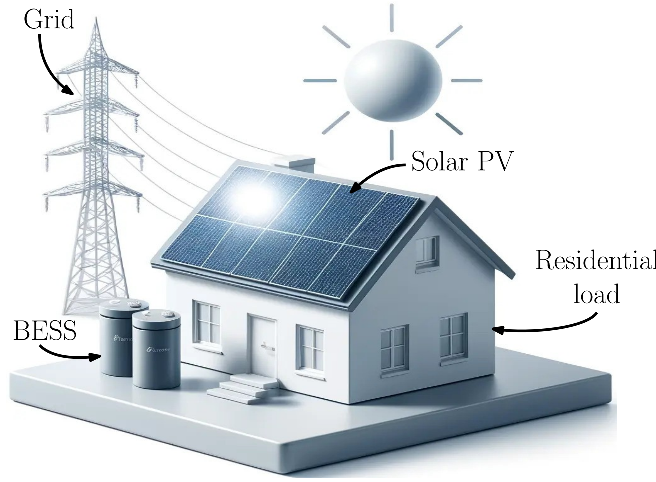


Fig. 1: Energy system model

they are highly sensitive to weather conditions such as air temperature and solar irradiance. To mitigate immediate fluctuations, current energy management practices deploy batteries as temporary storage solutions, balancing energy supply for a few hours up to a few days. This short-term management is supported by tools such as weather forecasting [9], [10], predictions of energy generation and consumption [11], [12], and sophisticated real-time monitoring and control systems [13].

However, these methods are inadequate for predicting or ensuring long-term performance and reliability. With climate change inducing more frequent extreme and unpredictable weather patterns, such as extended rainy seasons followed by long periods of intense sunshine, existing battery systems often fall short. They may manage the intermittent fluctuations of energy supply and demand adequately but struggle with prolonged deviations in weather. This results in potential stability issues for the grid during extended adverse conditions. Therefore, it becomes imperative to develop a new approach that incorporates stochastic modelling to better manage these challenges and ensure grid stability.

IV. Background

Distributed energy resources [14], such as solar PV panels, are vital to modern energy systems, providing clean, renewable, and locally generated power. These decentralised, modular technologies provide flexibility and enhance power system resilience by being deployed near the point of use. Despite their advantages, solar panels are extremely sensitive to environmental factors such as temperature and solar irradiance, which significantly influence their efficiency.

The efficiency of solar panels decreases with rising temperatures, resulting in higher thermal losses and diminished output [15]. This sensitivity is quantified by the temperature coefficient, which indicates the reduction in energy production for each degree Celsius increase above 25°C. Additionally, solar efficiency is greatly affected by solar irradiance, which varies with weather conditions like cloud cover, rain, snow, and fog. Both temperature and solar irradiance are crucial for

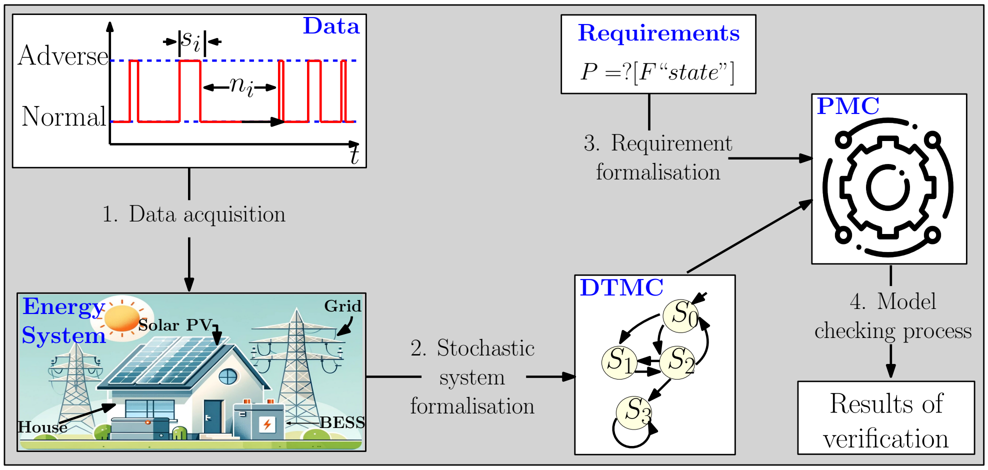


Fig. 2: High-level diagram of the approach

calculating the power output of a PV module, as illustrated by the following equation [16]:

$$P_{PV} = W_{PV} \cdot f_{PV} \cdot \left(\frac{G_T}{G_{STC}}\right) \cdot (1 - \alpha_p(T_c - T_{C,STC})) \quad (1)$$

where P_{PV} is the power output of the PV module (kW), W_{PV} is the peak power output of the PV module (kW), f_{PV} is the PVs derating factor (%), G_T is the solar irradiance on the PV module in the current hour (kW/m²), G_{STC} is the solar irradiance under standard test conditions (1 kW/m² at 25 °C), α_p is the power temperature coefficient, T_c is PV's panel temperature (°C) and $T_{C,STC}$ is the PV cell temperature under standard conditions (°C).

Temperature fluctuations, particularly during heatwaves, can accelerate the degradation of PV cells, reducing their lifespan and efficiency over time. The unpredictable nature of these effects poses challenges in maintaining consistent energy output and system reliability, highlighting the necessity for a robust approach to manage these uncertainties.

Stochastic model checking (also known as probabilistic model checking) [17] is a formal verification technique used to analyse systems that exhibit probabilistic behaviour. It extends traditional model checking by incorporating probabilistic models (e.g., Markov chains) to evaluate the likelihood of events within a system. This approach is particularly useful for systems where uncertainty and randomness are significant, such as in network protocols, biological processes, and reliability engineering [18], [19]. Stochastic model checking uses algorithms to verify whether a system satisfies specified quantitative properties, such as probabilities, expected values, and reward measures, enabling the assessment of both performance and dependability under uncertainty [20].

A common model used in stochastic model checking is the Discrete-Time Markov Chain (DTMC) [21]. DTMCs represent systems undergoing transitions from one state to another at discrete time steps, with each transition occurring according to a specified probability. Probabilistic Computation Tree Logic (PCTL) [22] is a temporal logic used to define properties of probabilistic models like DTMCs. It extends Computation Tree Logic (CTL) by incorporating probabilistic operators, enabling the expression of quantitative properties. For instance, PCTL can specify the probability that a certain condition will eventually hold or that it will remain true for a given number of steps. This makes PCTL a powerful tool for formally verifying that probabilistic systems meet desired specifications, such as performance guarantees and reliability criteria.

Stochastic model checking is particularly suited for addressing the problem of long-term impacts of weather on DERs such as solar PV panels. By capturing and analysing the inherent stochasticity of weather conditions, stochastic model checking can explore all possible scenarios and quantify the likelihood of different outcomes. Through this method, we can better understand and predict the cumulative effects of weather variability, ultimately enhancing the reliability and resilience of the system. For more information regarding the formal definition of DTMCs and PCTL, we refer the reader to the following sources [17], [23].

V. Approach

We outline our systematic approach for analysing the resilience of DERs against adverse weather conditions in Figure 2, comprising the following four key steps:

1. Data acquisition: This initial step involves collecting essential weather data, such as air temperature and solar irradiance, known to significantly impact system performance. While these parameters are the primary focus of this work, we acknowledge that other factors, such as air pollution, may also affect solar output. However, in this study, we focus solely on available historical weather data, with seasonal variations implicitly captured through the patterns in solar irradiance and temperature. The collected data is then used to simulate the system's behaviour under varying conditions, facilitating an in-depth analysis of performance impacts.

2. Stochastic system formalisation: We create a formal model to capture the uncertainties and variability inherent in the system's behaviour. For this purpose, we use a DTMC to

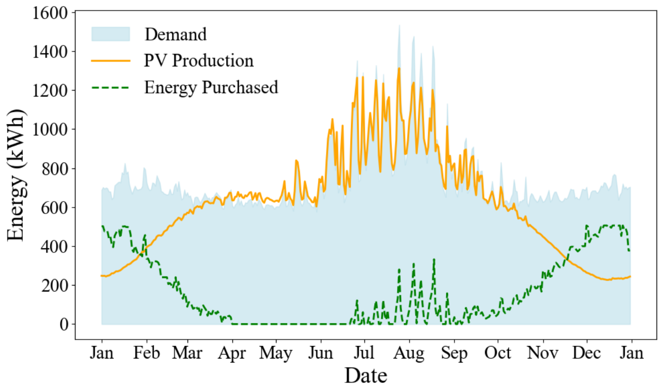


Fig. 3: Daily energy demand (shaded area), total PV production (solid line), and energy purchased (dashed line) illustrate how PV production meets demand and when grid energy purchases are necessary.

encapsulate the variability of weather affecting the solar panel system. DTMCs are particularly well-suited for our analysis because they align with the discrete intervals at which weather data is typically collected, allowing us to effectively model system behaviour over time. While other models, such as CTMCs and MDPs, also exist, they are more appropriate for continuous processes (CTMCs) or introduce additional complexity related to decision-making under uncertainty (MDPs). The validity of the model is confirmed by domain experts.

3. Requirement formalisation: This step precisely defines and verifies the system's desired performance metrics and properties under varying conditions. Using PCTL, we formalise requirements ranging from basic correctness to complex quantitative measures, such as:

- Natural language: *The system should have at least 0.8 probability of reaching the desired state under specified conditions.*
- PCTL: $P_{\geq 0.8}[\mathbf{F}\,(\text{desired\_state})]$. Where $\mathbf{F}$ denotes that the system will eventually reach the desired state, and with a probability greater or equal to 0.8 ($P_{\geq 0.8}$).

4. Model checking process We employ the probabilistic model checker PRISM [24] to validate our system model against the formalised requirements. PRISM performs a thorough state-space exploration to verify the system's compliance with the specified properties under various scenarios. This rigorous evaluation assesses the system's long-term resilience and identifies areas for potential improvement, ensuring robust performance across diverse conditions. It is important to note that our approach does not mandate the use of a specific probabilistic model checker; alternatives like Storm (https://www.stormchecker.org/) could also be considered.

The above steps provide a comprehensive framework for assessing the impact of weather variability on DERs, enhancing our ability to predict system behaviour and ensuring sustained resilience and performance.

VI. Preliminary evaluation

To evaluate our approach, we implemented a Matlab simulation of the system described in Section III using MILP optimisation [25]. The simulation ensures that load demand is met at every instant with minimal operational cost, guaranteeing reliable and affordable power supply to the end-user.

In step 1, we used one-year data from London in 2022, sourced from Open-Meteo [26]. We chose this period due to the UK's rare heatwave, with temperatures reaching 40°C, to analyse its impact on solar panel performance and the energy system. The data includes hourly air temperature and solar irradiance, integrated into our simulation to estimate energy generation, battery interactions, and grid transactions. We also included one-year demand data for a London house to compare production with demand. Adverse weather was defined as temperatures of 25°C or above, focusing on heatwaves rather than other conditions like extreme cold or heavy rainfall.

Figure 3 depicts the daily energy demand and energy generated by PV solar panels throughout the year. As shown, solar generation peaks during the summer months, while winter months see the least power production due to the variation in solar irradiance. The surplus state occurs when energy generation exceeds demand, whereas during the request state energy is purchased from the grid to meet the load demand.

In step 2, we synthesised a DTMC, as shown in Figure 4, to represent our simplified power system's behaviour. We began by identifying its primary operational states, focusing on solar panel performance under *normal* and *adverse* weather conditions, and meticulously examined the transitions between them. This DTMC model was achieved after multiple rounds of refinement, incorporating feedback from domain experts and additional system observations. Our observations revealed that solar energy generation could either exceed or fall short of demand. Based on this, we defined two system states: *surplus* and *request*. In the surplus state, excess energy after meeting demand is used to either *charge the battery* or *sell to the grid*. Conversely, in the *request* state, when PV generation is insufficient, the system either *discharges the battery* (if energy is stored) or *purchases energy* from the grid.

To determine the transition probabilities, we analysed hourly data from the Matlab simulation. By examining the frequency of state transitions, we calculated the probabilities of moving between states. This analysis ensured our DTMC accurately reflects the stochastic nature of the power system's behaviour under varying weather conditions. Unexpectedly, we observed higher probabilities of transitioning to a surplus state during adverse weather (0.85) compared to normal weather (0.37), as shown in Figure 4. This was due to increased solar PV production during summer, despite higher degradation rates. While this degradation is not addressed in our current work, it is a key observation for future research.

Step 3 involved selecting system properties for preliminary evaluation, expressed in both natural language and PCTL, as shown in Table I. In step 4, we verified these properties through probabilistic model checking, assessing system re-

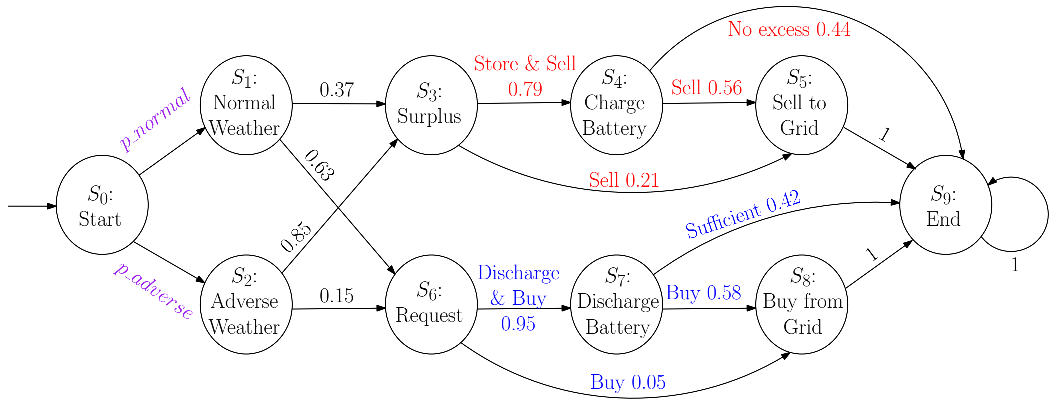


Fig. 4: Derived DTMC from our simplified energy system model

quirements and identifying any violations. For our analysis, we varied the probabilities of normal and adverse weather within the range of $[0, 1]$ in 0.1 increments. The results, illustrating how these probabilities impact system performance, are presented in Figure 5. Note that only the probability of normal weather (p_normal) is shown in the graphs, as the probability of adverse weather is simply $1 - p\_normal$, making the inclusion of $p\_adverse$ counter-intuitive.

In the first graph, we observe the probability values for the property $P = ?\ [\ F\ state = buy\_from\_grid\ ]$ as the probabilities of normal and adverse weather change. This helps us determine the likelihood of buying energy from the grid based on weather conditions. The graph shows that normal weather correlates with a higher likelihood of buying from the grid, while adverse weather decreases this likelihood. In our DTMC model (Figure 4), we see that higher probabilities of adverse weather increase the likelihood of reaching the upper part of the model (0.85 vs. 0.15), corresponding to higher energy generation. This observation is useful for understanding how weather changes can lead to higher costs, as energy is more frequently purchased from the grid during normal weather when generation is lower.

The second graph illustrates a different outcome. As the probability of normal weather increases, the probability of the property $P = ?\ [\ state < request\ U\ state = end\ ]$ decreases. This property reflects the likelihood of reaching the end state without requesting energy, i.e., without visiting the states in the model's bottom branch (see Figure 4). In simpler terms, it indicates reaching the *surplus* state and then transitioning to *charge_battery*, *sell_to_grid*, or both before the end state. In the DTMC model, higher probabilities of normal weather increase the likelihood of reaching the bottom part of the model (0.63 vs. 0.37), thereby decreasing the probability of satisfying this property. This observation is crucial for planning ahead to balance revenue with cost.

The property $P > 0.8\ [\ F\ state = surplus\ ]$ evaluates to a boolean condition and is satisfied only for normal weather probabilities of 0 or 0.1. This indicates that the probability of reaching the *surplus* state is below 0.8 for higher normal weather probabilities. In the DTMC model (Figure 4), reaching the *surplus* state is more likely under adverse weather (0.85) than normal weather (0.37). The 0.8 threshold ensures that the system remains in a surplus state for over 80% of the time, thereby minimising energy purchase costs. This value is used in the case study to evaluate system performance under varying weather conditions and can be adjusted to meet specific system requirements and guide design decisions.

Our preliminary evaluation using probabilistic model checking highlights the impact of varying weather conditions on DER performance. These findings emphasise the importance of considering weather variability when assessing the long-term resilience and performance of DER systems. For example, if the probability of buying energy from the grid is high and the budget is limited, one could either increase the budget or invest in additional solar panels or wind turbines. Understanding the impact of weather on solar panels enables proactive measures. During adverse weather, like heatwaves, surplus energy is more likely, but so is performance degradation. Adaptive measures, such as cooling PV panels, can mitigate this. Incorporating degradation rates into the probability model accounts for solar PV wear and tear under adverse conditions. Conversely, during normal weather, lower energy production requires preparation to purchase additional energy. Predicting how adverse weather will affect energy production over time is crucial for informed decision-making and system optimisation, enhancing resilience.

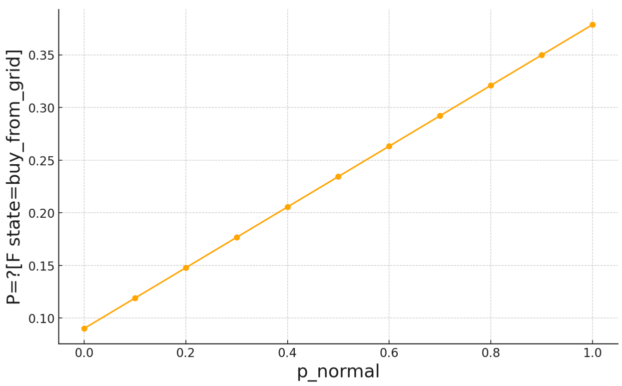
VII. Conclusion

In this work, we introduced an approach that leverages stochastic modeling and analysis to evaluate the long-term performance and resilience of DERs under adverse weather conditions. By incorporating DTMCs and PCTL, we offer a rigorous framework for assessing the probabilistic impacts of weather variability on solar PV systems. This approach facilitates a comprehensive understanding of cumulative effects, crucial for optimising system performance and making informed decisions. Our preliminary evaluation using the PRISM model checker demonstrates that this method effectively provides insights into long-term system performance trends.

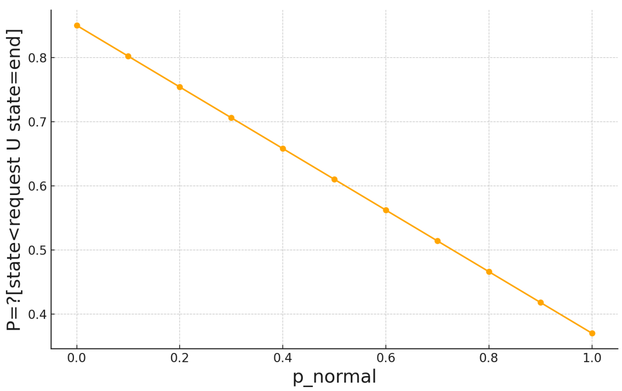
Future work will extend our methodology to include adaptive mechanisms that dynamically respond to changing weather conditions, further enhancing power system resilience.

TABLE I: Energy system properties expressed in both natural language and PCTL, where P is the probabilistic operator, ? is the condition evaluation operator, $<$ is a relational operator, = is an equality operator, F stands for eventually (future), U means until, and *state* refers to a specific status of the system at a given point in the probabilistic model.

Property description	PCTL
What is the probability of buying energy from the grid?	$P = ?\ [\ F\ state = buy\_from\_grid\ ]$
Is the probability of eventually reaching the surplus state greater than 0.8?	$P > 0.8\ [\ F\ state = surplus\ ]$
What is the probability of eventually reaching the end state without requesting energy?	$P = ?\ [\ state < request\ U\ state = end\ ]$



(a) $P = ?\ [\ F\ state = buy\_from\_grid\ ]$



(b) $P = ?\ [\ state < request\ U\ state = end\ ]$

Fig. 5: Output of PRISM's property verification while varying the normal weather probability from 0 to 1 in 0.1 steps. The graphs show how the probabilities of normal weather and adverse weather ($1 - p\_normal$) affect the two properties of interest. Property (a) demonstrates a high probability of buying from the grid as the likelihood of normal weather increases. Property (b) shows that the probability of not requesting additional energy (e.g., via battery discharge or grid purchase) decreases with increasing normal weather probability.

We also plan to incorporate cost-effectiveness analyses, evaluating optimal grid interactions and battery usage within budgetary constraints. Additionally, we aim to apply our approach to other DERs, such as wind turbines, for a more comprehensive assessment of renewable energy systems.

References

[1] John Lubbock. Government figures show a 6.7% increase in the uk's solar capacity in last year. https://shorturl.at/kHoNJ, 2023.

[2] Manish Kumar and Arun Kumar. Performance assessment and degradation analysis of solar photovoltaic technologies: A review. *Renewable and Sustainable Energy Reviews*, 78:554–587, 2017.

[3] Sanaz Ghazi and Kenneth Ip. The effect of weather conditions on the efficiency of pv panels in the southeast of uk. *Renewable energy*, 69:50–59, 2014.

[4] Alessandro Trindade and Lucas Cordeiro. Automated formal verification of stand-alone solar PV systems. *Solar Energy*, 193:684–691, 2019.

[5] Min Gao et al. Prob. model checking & scheduling for energy router in green cities. *IEEE Transactions on Industrial Informatics*, 14(4):1501–1510, 2018.

[6] Alan Ransil et al. Improving system resilience through formal verification of transactive energy controls. In *PES TESC*, pages 1–5, 2020.

[7] Yan Li et al. Distributed formal analysis for power networks with deep integration of DERs. *IEEE Transactions on Power Systems*, 34(6):5147–5156, 2018.

[8] Gayathri Sugumar et al. Supervisory energy-management systems for microgrids: Modeling and formal verification. *IEEE Industrial Electronics Magazine*, 13(1):26–37, 2019.

[9] Hanmin Sheng et al. Short-term solar power forecasting based on weighted gaussian process regression. *IEEE Transactions on Industrial Electronics*, 65(1):300–308, 2017.

[10] Hangxia Zhou et al. Short-term PV power forecasting based on long short term memory NN and attention mechanism. *Ieee Access*, 7:78063–78074, 2019.

[11] Ruilong Deng et al. Survey on DR in smart grids: Math models & approaches. *IEEE Transactions on Industrial Informatics*, 11(3):570–582, 2015.

[12] Pierluigi Siano and Debora Sarno. Assessing benefits of residential demand response in a real time distribution energy market. *Applied Energy*, 161:533–551, 2016.

[13] Aditya Sundarajan et al. An Intelligent Smart Grid Switching System for an Efficient Load Balancing Through ML Models. *Smart Grids as Cyber Physical Systems*, 1:111–122, 2024.

[14] Mudathir Funsho Akorede et al. Dist. energy resources and benefits to the environment. *Renewable and Sustainable Energy Reviews*, 14(2):724–734, 2010.

[15] Antoni Martiniano A. Acuzar et al. Effects of weather and climate on renewable energy resources in a distributed generation system simulated in visayas, philippines. In *IEEE HNICEM*, pages 1–6, 2017.

[16] Nallapaneni Manoj Kumar et al. Hybrid renewable energy microgrid for a residential community: A techno-economic and environmental perspective in the context of the sdg7. *Sustainability*, 12(10):3944, 2020.

[17] Marta Kwiatkowska, Gethin Norman, and David Parker. *Stochastic Model Checking*, pages 220–270. Springer Berlin Heidelberg, 2007.

[18] Marta Kwiatkowska, Gethin Norman, and David Parker. Probabilistic model checking: Advances and applications. *Formal System Verification: State-of the-Art and Future Trends*, pages 73–121, 2018.

[19] Marta Kwiatkowska. Quantitative verification: models techniques and tools. In *ESEC-FSE companion*, pages 449–458, 2007.

[20] Radu Calinescu, Carlo Ghezzi, Marta Kwiatkowska, and Raffaela Mirandola. Self-adaptive software needs quantitative verification at runtime. *Communications of the ACM*, 55(9):69–77, 2012.

[21] William J. Stewart. *Probability, Markov Chains, Queues, and Simulation: The Mathematical Basis of Performance Modeling*. Princeton University Press, 2009.

[22] Frank Ciesinski and Marcus Größer. *On Probabilistic Computation Tree Logic*, pages 147–188. Springer Berlin Heidelberg, 2004.

[23] Christel Baier and Joost-Pieter Katoen. *Principles of model checking*. MIT Press, 2008.

[24] Marta Kwiatkowska, Gethin Norman, and David Parker. Prism 4.0: Verification of probabilistic real-time systems. In *Computer Aided Verification*, pages 585–591, 2011.

[25] Ankita Garg et al. Techno-economic-environmental analysis for net-zero sustainable residential buildings. In *ISGT EUROPE*, pages 1–5, 2023.

[26] OpenMeteo. Openmeteo: Free weather api. https://open-meteo.com/, 2024. Accessed: 2024-06-18.

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