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A Stochastic Framework for Enhancing Smart Grid Reliability under Solar Generation Uncertainty in Keeping with Emission Standards

As the world transitions toward carbon-neutral energy systems, the integration of solar photovoltaic (PV) power into smart grids (SGs) becomes essential. However, the stochastic nature of solar irradiance poses significant challenges to grid reliability. This chapter presents a comprehensive stochastic framework that models solar generation uncertainty and evaluates its impact on SG reliability using probabilistic indices: such as the loss of load probability (LOLP), defined as a function of discrete probability of demand mismatch in the generator and load; and expected energy not supplied (EENS), defined as a sum of probabilistic variation in the discrete load connected to the generating unit consisting of both conventional and solar distributed generation. A multi-period optimization approach is developed to minimize system cost, emissions and unreliability. The proposed approach supports the strategic integration of renewable energy into power systems, while aligning with the carbon neutrality objectives outlined in the United Nations sustainable development goals (SDGs).

1.1. Introduction

The transition to a sustainable and decarbonized energy future is a key component of the United Nations SDGs, particularly SDGs 7 (Affordable and Clean Energy) and 13 (Climate Action). As countries attempt to cut greenhouse gas emissions and attain carbon neutrality, the use of renewable energy sources (RES), particularly solar power, is becoming more common. However, the inherent fluctuation and uncertainty in solar energy generation pose major risks to the

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reliability and stability of electrical power networks. SGs, which are outfitted with advanced monitoring, communication and control technology, present a promising alternative for integrating RES while ensuring system dependability.

Nonetheless, uncertainties in solar irradiance caused by weather fluctuations, seasonal variations and forecasting constraints can degrade the efficiency of even the most sophisticated SG systems. Ensuring grid resilience in these conditions is important for attaining solar energy's full potential and working toward global decarbonization targets.

Figure 1.1 depicts the dynamic interaction of solar energy generation with SG operations, with an emphasis on dependability and sustainability. Solar panels generate electricity from sunlight, a clean and sustainable source; nevertheless, the power output is fundamentally unpredictable due to weather variations such as cloud cover and rain. This unpredictability challenges grid reliability, which is addressed by solar generation forecasting systems. These systems employ meteorological data to forecast future solar production, but forecasting errors can still result in mismatches between energy supply and demand. The SG controller is critical for handling these uncertainties. It uses real-time data from solar producers, weather forecasts and consumer demand to optimize electricity delivery. In the event of supply fluctuations, the controller uses energy storage equipment, such as batteries, to store excess energy or provide more power when solar production is insufficient. The buffering capability improves grid stability. Furthermore, the system continuously assesses performance using reliability indicators like LOLP and EENS, which quantify the danger of power outages. Finally, the integration of forecasting, energy storage and smart control technologies enables a resilient grid that supports increasing reliance on solar power while also aligning with global SDGs, particularly the goal of carbon neutrality. This chapter studies the effect of solar power uncertainty on SG dependability and proposes mitigation measures such as energy storage, real-time demand response and probabilistic forecasting. It also assesses how these technological and operational solutions correspond with the larger goals of carbon neutrality and sustainable growth.

In this context, evaluating and enhancing the reliability of SGs becomes a critical objective. Key reliability indicators such as LOLP and EENS are commonly used to quantify the likelihood and impact of power supply failures. These metrics provide a probabilistic measure of system performance under variable generation and load conditions. To estimate these indices, advanced probabilistic modeling, Monte Carlo simulations and Markov processes are typically employed. By integrating these methods with real-time data and forecasting tools, SGs can proactively manage uncertainty in solar generation, thereby maintaining system resilience and ensuring a reliable supply of electricity in line with carbon neutrality objectives.

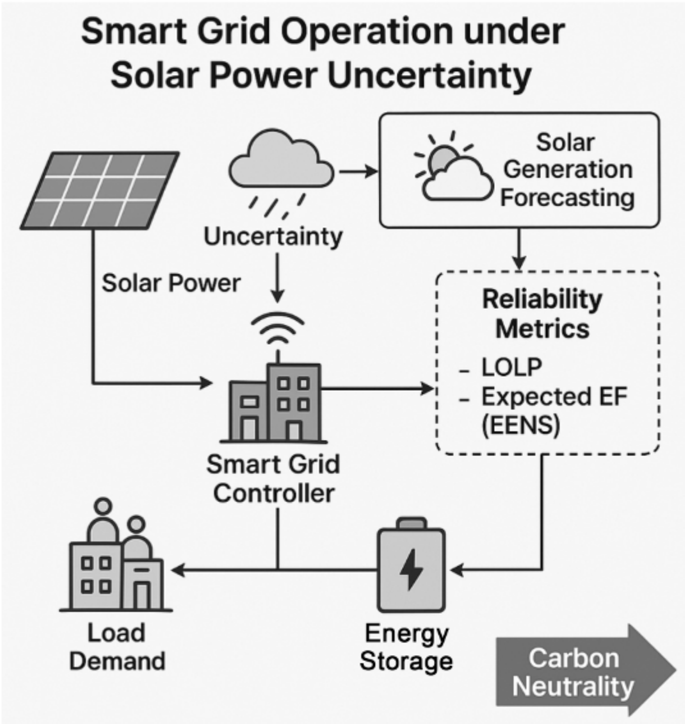

Figure 1.1. *Smart grid operation under solar power uncertainty (adapted from Khalkho et al. (2022), under CC BY 4.0.)*

1.2. Literature review

Khalkho et al. (2022) propose a multistate model that integrates random variations in solar irradiance to improve SG dependability in the face of solar power generation uncertainty. This novel probabilistic modeling assesses reliability metrics such as LOLP and anticipated energy not served (EENS). By incorporating solar PV generation, the study highlights its potential to improve carbon neutrality, demonstrating that replacing conventional coal-based generation with solar energy significantly contributes to the SDGs of reducing carbon emissions and achieving carbon zero. Moreno et al. (2017) underline the need of planning electrical systems under uncertain conditions, particularly in terms of solar power generation prices. It calls for a new optimization paradigm that uses operational flexibility and SG technology to improve reliability. The approach intends to optimize investments in RES by modeling uncertainties and operational restrictions, while also complying with carbon neutral development goals. This method helps to avoid inefficient investments and promotes the transition to a low-carbon energy system. Gidiagbaa et al. (2023) underlines the importance of reliability engineering in improving renewable energy systems, such as solar power, in the face of uncertainty. It highlights how upcoming technologies like artificial intelligence (AI) and predictive maintenance improve reliability, helping to achieve SDGs such as carbon neutrality. By addressing issues with energy output consistency, the study provides actionable recommendations for policymakers and engineers to ensure robust solar energy systems, ultimately supporting the transition to a resilient and sustainable energy future aligned with carbon neutrality goals. Zhou et al. (2023) present that a global desert-based PV power network could reliably meet worldwide electricity demand while supporting carbon neutrality and causing far less warming than continued fossil-fuel use Abdelghany et al. (2023) use formal methods to analyze smart-grid reliability, providing rigorous mathematical modeling of grid failure modes and mitigation strategies.

Zhou et al. (2023) does not expressly address SG stability in the face of unpredictability in solar power generation. However, it envisions a worldwide solar network that uses desert PVs to supply electricity demand, emphasizing the possibility of reliable power transmission between continents. This network attempts to phase out carbon emissions in accordance with the SDGs of carbon neutrality. The findings indicate that, while solar energy generation is diurnally uneven, transcontinental power transmission may efficiently regulate this fluctuation, hence improving energy supply reliability. Bienstock et al. (2013) investigate SG resilience under uncertainty, notably with fluctuating renewable resources such as solar electricity. It introduces the Chance Constrained Optimum Power Flow (CC-OPF) model, which reduces the risks associated with these variations while ensuring high probability compliance with operational requirements. This method is consistent with the SDGs of carbon neutrality by optimizing the integration of RES while maintaining grid stability, so facilitating the transition to a more resilient and sustainable energy system. Zhang et al. (2024) underline the significance of establishing a new power system based on RES such as solar to attain carbon neutrality in China by 2060. The report emphasizes that current energy systems cannot provide basic energy needs without exceeding planetary boundaries, and that implementing a new power system might lessen pressures on these boundaries by up to 30% by 2050, thereby supporting sustainable development objectives. Garg et al. (2024) propose a two-pronged strategy for improving SG reliability in the face of uncertainty, combining competitive market processes with cooperative initiatives. It focuses on increasing distribution network resilience, particularly during unpredictable events in solar power generation. The strategy, which uses battery storage facilities, reduces carbon footprints by up to 97% while preserving overall profit, consistent with SDGs of carbon neutrality. This comprehensive strategy efficiently addresses the difficulties and uncertainties surrounding RES. Onu et al. (2023) underline the necessity of incorporating RES, specifically solar electricity, into SGs to improve dependability and resilience. It examines the issues caused by uncertainty in solar energy, as well as the impact on grid stability and power quality. By focusing on SDGs such as carbon neutrality, the study advocates for strong policies and strategies that prioritize RES integration, ultimately supporting a decarbonized future while addressing the technical, economic and regulatory aspects of SG development.

Joseph (2023) underlines that reaching carbon neutrality through the renewable energy transition requires careful planning and coordination of generation resources to ensure grid resilience. It emphasizes the necessity of both resource adequacy and operational stability, particularly when incorporating variable RES such as solar power. Addressing uncertainty in solar generation is critical for ensuring stable grid operations while reaching climate targets and achieving SDGs for a decarbonized electric system. Dan et al. (2022) examine the operational risks associated with incorporating new energy sources, such as solar power, into the power system, particularly in the face of energy swings. It presents probabilistic operational risk indicators that take into consideration the features of new energy integration and AC-DC hybrid transmission. This method is consistent with the SDGs of carbon neutrality by tackling rising operational risks and improving the reliability of SGs in the context of RES. Liu et al. (2023) emphasize that just expanding wind and solar capacity is unsuccessful in enhancing reliability in zero-carbon power networks due to transmission congestion and spatiotemporal differences in vulnerability. It underlines the need for 61–105% more firm, zero-emission capacity to ensure system reliability, especially in the face of climate and technology uncertainty. This is consistent with the SDGs of carbon neutrality by pushing for a holistic approach that takes into account operational restrictions as well as the dynamic nature of renewable resource availability. Sarwat et al. (2015) present a novel technique for assessing SG reliability that takes into account fluctuating weather conditions, which is critical for evaluating the uncertainty of solar power output. The study uses the variable weather Boolean logic driven Markov process (VW-BDMP) to integrate renewable resources, including solar energy, while improving reliability in line with SDGs such as carbon neutrality.

This method provides a complete framework for assessing future power system reliability in the face of unpredictable weather conditions. Yu et al. (2023) assess the derivative value of SG investment, highlighting its significance in supporting renewable energy and achieving SDGs such as carbon neutrality. It emphasizes the importance of SG resilience, especially given the uncertainties in solar power generation. The assessment index system comprises performance indicators that analyze the grid’s ability to sustain operational stability and efficiency, which are critical for promoting renewable energy integration and ensuring the grid's resilience in the face of fluctuating energy sources. Sun et al. (2024) address dependability issues in microgrids due to the unexpected nature of solar power generation. It presents a data-driven uncertainty set that use a neural network to improve reliability while reducing unrealistic worst-case situations. This strategy supports SDGs by optimizing RES and contributes to carbon neutrality. The proposed two-stage robust optimization model successfully regulates power dispatch, ensuring economic viability and better convergence performance, so facilitating the transition to dependable and sustainable energy systems. Shankar et al. (2024) address SG reliability by combining the Internet of Things (IoT) and hedge systems to mitigate volatility in solar power generation. The suggested solution improves grid stability and solar energy output reliability through the use of machine learning algorithms and predictive analytics. This is consistent with the SDGs of carbon neutrality by encouraging efficient renewable energy use, lowering dependency on fossil fuels and supporting the transition to sustainable energy systems. Buonanno et al. (2021) address uncertainties in solar power generation, which can have a considerable impact on the reliability of SGs. It models these risks using a scenario-generation approach to optimize the functioning of distributed energy resources (DERs). This strategy supports SDGs, particularly carbon neutrality, by increasing the use of RES. The findings show that SGs can increase reliability and efficiency, allowing the transition to sustainable energy systems while controlling the inherent fluctuation of solar irradiance.

Cepin (2019) analyzes the dependability of SGs, particularly with regard to intermittent power generation sources such as solar energy. It emphasizes the issues posed by rising complexity in SGs, which can result in far-reaching implications from infrequent malfunctions. While the article does not specifically address carbon neutrality or the SDG, it underlines the importance of sophisticated reliability approaches in evaluating future SGs to ensure they can efficiently integrate RES while maintaining dependability and security. Kabeyi et al. (2023) describe how SG technologies improve dependability by allowing for a two-way flow of electricity and information, which is critical given the uncertainty of solar power generation. SGs increase power system efficiency and demand management by including variable renewables such as solar. This is consistent with SDGs, as it promotes energy security and economic growth while also helping to mitigate climate change, ultimately contributing to carbon neutrality initiatives. Abdual Baseer et al. (2023) propose a renewable intelligent grid model that combines solar power generation, battery energy storage (BES) and wind systems to improve SG stability. It emphasizes the importance of stability and outage mitigation, which is consistent with SDGs such as carbon neutrality. The model employs a boost converter optimized by the horse herd optimization algorithm (HOA) to improve efficiency, minimize total harmonic distortion (THD) and improve metrics such as EENS, hence promoting sustainable energy generation.

According to Khan et al. (2021), SGs improve solar power generating reliability by maximizing the use of RES and optimizing storage. This is consistent with the SDGs, notably carbon neutrality, as it addresses inconsistencies in energy generation and increases consumption efficiency. SGs help to create a more sustainable energy future by allowing for flexible transmission and distribution, which is critical in solving the problems faced by climate change and rising energy demand. Sam et al. (2024) address SG reliability in the face of uncertainties in solar power generation or carbon neutrality. However, it investigates how sustainability measures affect solar energy investment in Ghana, confirming a quadratic link between environmental uncertainty and solar energy investment. The findings contribute to SDGs, particularly SDG 7, by boosting renewable energy legislation. The integrated model produced could influence plans for increasing solar energy investments in the face of environmental uncertainty, indirectly contributing to carbon neutrality initiatives.

Ding et al. (2022) examines the sustainability of PV installations in terms of carbon neutrality, highlighting the need of dependable power output. It creates a sustainability evaluation index system that covers technical, economic and environmental variables that are critical in determining the dependability of solar power output. While it does not particularly address SG dependability under uncertainty, it emphasizes the importance of appropriate evaluation methodologies in achieving sustainable development targets such as carbon neutrality in PV installations.

Ahangar et al. (2018) assess SG resilience while taking into account uncertainties in renewable resources, such as solar power output. It stresses the role of cyber network topologies in improving dependability indices, which is consistent with carbon neutrality aims for sustainable development. By examining the interdependence of cyber and power networks, the suggested method addresses the effects of cyber failures on dependability, ultimately facilitating the transition to a more resilient and sustainable energy system that contributes to carbon neutrality goals. Canizes et al. (2018) explore the complexity of long-term SG planning under uncertainty, with a special emphasis on renewable sources such as solar power. It emphasizes that incorporating combined heat and power (CHP) units can improve network dependability, reduce projected energy outages and reduce power losses.

This correlates with SDGs, such as carbon neutrality, by promoting clean generation devices and reducing the need for additional power lines, so supporting environmental objectives while addressing uncertainties in solar power generation.

Author(s) and Year	Focus area	Method/ model	Reliability metrics	Contribution to SDGs (carbon neutrality)	Solar prediction method/accuracy metric
Khalkho et al. (2022)	Smart grid reliability under solar uncertainty	Multistate probabilistic model	LOLP, EENS	Solar PV integration replacing coal enhances carbon neutrality	Markov-based probabilistic modeling; prediction accuracy not specified
Gidiagba et al. (2023)	Reliability engineering in renewables	Predictive maintenance, AI	Not specified	Boosts solar system stability and policy guidance	Predictive maintenance; forecast detail not specified
Zhou et al. (2023)	Global solar power network	Desert PV with transcontinental transmission	Not specified	Balances solar variability for stable global supply	Diurnal solar variability addressed; no prediction model used
Zhang et al. (2024)	China's new energy system for 2060	System transformation analysis	Not specified	Reduces ecological pressure and promotes solar use	Strategic planning approach; solar prediction not detailed
Garg et al. (2024)	Solar distribution network resilience	Market + cooperative strategy, battery use	Not specified	Achieves 97% carbon footprint reduction	Real-time battery response; solar prediction not central
Onu et al. (2023)	RES integration in smart grids	Policy and regulatory strategies	Grid stability, power quality	Supports solar integration and low-carbon future	No explicit solar prediction model discussed
Joseph (2023)	Generation planning for carbon neutrality	Coordination and resource adequacy	Not specified	Aligns planning with SDG climate targets	Resource adequacy focused; solar prediction not discussed
Dan et al. (2022)	Risks from new energy integration	Probabilistic risk indicators	Not specified	Enhances grid resilience to energy fluctuations	AC-DC transmission focus; prediction details not given
Liu et al. (2023)	System-wide reliability	Capacity adequacy modeling	Not directly specified	Advocates for firm zero-emission capacity	Requires higher firm capacity due to prediction uncertainty

Yu et al. (2023)	Smart grid investment value	Evaluation index system	Efficiency, stability metrics	Supports smart grid-driven solar adoption	Grid-level solar variability included; prediction detail minimal
Sun et al. (2024)	Microgrid solar reliability	Neural network, robust optimization	Dispatch reliability, convergence	Enhances reliability via AI-based solar forecasting	Data-driven uncertainty set; robust prediction accuracy improved
Shankar et al. (2024)	IoT-based grid control	ML and predictive analytics	Grid stability, output consistency	Promotes efficient solar use and carbon reduction	Uses ML algorithms; prediction accuracy not numerically specified
Kabeyi et al. (2023)	Two-way smart grid under solar uncertainty	Smart grid technology integration	System efficiency, demand response	Supports energy security and carbon neutrality	Prediction methods not discussed
Abdual Baseer et al. (2023)	Renewable intelligent grid design	HOA-optimized boost converter	THD, EENS, system stability	Improves solar efficiency and outage mitigation	Solar output tracking; prediction methods not detailed
Sam et al. (2024)	Solar investment under uncertainty	Quadratic investment model	Not specified	Promotes SDG 7 via renewable energy policy	Environmental uncertainty focus; no forecast model used
Ding et al. (2022)	PV sustainability evaluation	Tech-economic-environmental index	Indirect via sustainability factors	Aligns PV design with SDG climate targets	Solar output sustainability focus; no forecast method used
Figuero et al. (2022)	Carbon neutrality scenarios	Uncertainty scenario expansion	Not specified	Addresses uncertainty in GHG projections	No specific solar forecast method discussed
Goyal et al. (2024)	Demand response in smart grids	Hidden Markov model, pricing	Battery optimization, demand shaping	Improves reliability while reducing emissions	Uncertainty in emissions, not solar irradiance

Table 1.1. *Smart grid reliability under solar power generation uncertainty and SDGs of carbon neutrality*

Figueroa et al. (2022) concentrate on forecasting carbon neutrality scenarios under uncertainty, emphasizing the development of a methodology that broadens the range of potential future scenarios. While it does not particularly address SG dependability or solar power generation, it does emphasize the increased uncertainty in cumulative GHG emissions and prices, which may have an indirect link to issues in integrating RES such as solar. The methodology tries to identify key situations and factors for achieving carbon neutrality. Goyal et al. (2024) discuss the issues of reliability in SGs under the uncertainty of RES, notably solar power. It emphasizes the use of demand response technologies and smart meters to reduce peak-hour demand pressures, so contributing to SDGs such as carbon neutrality. The suggested real-time price-based hidden Markov model and increased demand response techniques aim to optimize battery use and improve network dependability, in line with the goals of lowering emissions and operational costs in power generation.

Technique	Method description	Prediction horizon	Common tools/models	Specified error
Statistical methods	Use historical data to fit statistical relationships	Short-term (min to hour)	ARIMA, linear regression	Root mean square error (RMSE) 10–20%
Machine learning	Learns complex patterns from historical and real-time weather data	Short to mid-term	ANN, SVM, LSTM	RMSE: 8–15%, MAE: 5–10%
Physical models	Based on physical laws and satellite or sensor data	Day-ahead, hourly	NREL SAM, PVGIS	RMSE: 15–25%
Stochastic models	Probabilistic models incorporating uncertainty in solar behavior	Long-term planning	Markov chains, Gaussian, VW-BDMP	RMSE: 12–22%
Hybrid models	Combine physical and AI-based models for robust predictions	Short to medium term	Hybrid (ML + numerical models)	RMSE: 5–12%

Table 1.2. *Solar irradiance prediction techniques and their accuracy*

Ehnberg et al. (2021) explore SGs' contribution to SDGs, with a focus on long-term advantages in underdeveloped nations. While it does not particularly address solar power generation reliability in the face of uncertainty, it does emphasize the potential of SGs to improve electrical infrastructure, which is critical for attaining carbon neutrality. SGs can assist sustainable development by improving grid resilience and integrating RES, facilitating the transition to a more stable and carbon-neutral energy system.

Abdukhakimov et al. (2019) investigate the stability of SG networks by combining distributed renewable energy resources (DRERs), such as solar electricity, with storage devices (SDs). It demonstrates how incorporating these aspects improves power reliability while also contributing to SDGs like carbon neutrality. By lowering greenhouse gas emissions and energy waste, the combination of DRERs and SDs helps to build a more robust power grid, resolve uncertainties in solar power generation and promote a sustainable energy future. Table 1.1 explains SG reliability under solar power generation uncertainty and SDGs of carbon neutrality.

Solar irradiance prediction techniques and their accuracy is shown in Table 1.2. Although several studies have examined SG reliability under renewable uncertainty, a major research gap exists in integrating uncertainty in generation (conventional and solar) with load demands and sustainability objectives into a single, actionable model. This chapter addresses this gap by developing a comprehensive framework that probabilistically models solar output, evaluates grid reliability using indicators such as LOLP and EENS, and embeds emission constraints aligned with sustainability and carbon reduction goals. Additionally, the incorporation of real-time monitoring, energy storage dynamics and demand response under uncertainty makes this approach uniquely positioned to support both operational resilience and long-term sustainability planning.

1.3. Problem formulation

The increasing integration of solar PV systems into modern power grids is critical to meeting global climate targets, particularly the SDGs for affordable and clean energy (SDG 7) and climate action (SDG 13). However, the intermittent and uncertain nature of solar power generation poses dependability difficulties for SG operations. To maintain a continuous, consistent and clean energy supply, it is critical to enhance grid reliability under uncertainty while limiting carbon emissions, thereby matching technical performance with sustainability goals.

Let,

$P_{solar(t)}$: stochastic solar power output at time t;

$P_{gen(t)}$: power from conventional dispatchable generators;

$P_{storage(t)}$: power charged/discharged from storage;

$P_{load(t)}$: demand at time t;

$E_{emissions(t)}$: emissions from fossil-based generation;

θ: reliability index (e.g., probability of supply-demand balance, system resilience) $P_{gen(t)}$, $P_{storage(t)}$, $SOC(t)$, *and* $P_{slack(t)}$ (slack for unmet demand).

1.3.1. *Objective function*

We minimize the expected total cost including reliability penalties and carbon emissions, while achieving the target of carbon neutrality:

$$min\ E[\ \Sigma\_t\ (\ C\_gen(P\_gen(t))\ +\ C\_storage(P\_storage(t))\ +\ C\_slack(P\_slack(t))\ +\ \lambda\ \cdot\ E\_emissions(t)\ )\ ] \qquad [1.1]$$

1.3.1.1. *Constraints*

– Power balance:

$$P\_solar(t)\ +\ P\_gen(t)\ +\ P\_storage(t)\ =\ P\_load(t)\ +\ P\_slack(t), \forall\ t \qquad [1.2]$$

– Emission constraint for carbon neutrality:

$$\Sigma_t E_{emissions(t)} \leq\ E_{target}, where\ E_{target} \rightarrow\ 0\ for\ long - term\ carbon\ neutrality \qquad [1.3]$$

– Probabilistic solar constraint:

$$P\left(P_{solar(t)} \in\ \left[P_{min(t)}, P_{max(t)}\right]\right) \geq\ \alpha, \forall \qquad [1.4]$$

– Generator and storage operational limits:

$$SOC_{Min} \leq\ SOC(t) \leq\ SOC_{\mathrm{m}}\ \&\ P_{gen_{min}} \leq\ P_{gen(t)} \leq\ P_{gen_{max}} \qquad [1.5]$$

– Reliability threshold constraint:

$$\theta(t) \geq\ \theta_{\min}, \forall \qquad [1.6]$$

1.3.2. *Optimization of objective function*

The objective function aims to minimize the total system cost, which includes the cost of conventional generation, penalty cost due to unreliability (e.g. loss of load and unmet demand) and cost of emissions from fossil-fuel-based generation.

$$Min\, E\, [\sum (C\_gen(t) + C\_unrel(t) + C\_emissions(t))\,] \qquad [1.7]$$

where:

– *C_gen(t)*: cost of conventional generation at time t;

– *C_unrel(t)*: cost due to unreliability (based on LOLP/EENS);

– *C_emissions(t)*: cost associated with CO_2 emissions;

– *C_unrel(t)*: the calculation methodology involves data of load, outage of conventional generating unit and solar generation probability are obtained and converted into a frequency domain. After the convolution of above three data, they are reconverted to a time domain to decide on discrete load probability.

The model predictive control (MPC) framework is applied for dynamic optimization under short-term forecasting inputs.

– Power balance:

$$P\_solar(t) + P\_gen(t) + P\_storage(t) = P\_load(t) + P_{loss(t)} \qquad [1.8]$$

– Emission cap constraint:

$$\sum E\_emissions(t) \leq Threshold\_CO2 \qquad [1.9]$$

– Reliability constraint:

$$\theta \geq \theta_{min}(e.g. LOLP \leq target) \qquad [1.10]$$

The core contribution of this study lies in the integration of solar power uncertainty modeling into the real-time optimization of SG operations. By developing a reliability-index-driven cost function that incorporates conventional generation costs, emission penalties and reliability metrics such as LOLP and EENS, the proposed framework offers a holistic approach to system-level optimization. Unlike traditional methods, this study leverages probabilistic models – including Gaussian and Markov-based distributions – to represent solar irradiance variability, ensuring more accurate and dynamic responses to fluctuations. Additionally, the framework embeds emission constraints aligned with carbon neutrality targets, bridging operational control with sustainable development objectives. A significant novelty is the fusion of planning-stage uncertainty modeling with real-time operational adjustments, made possible through the integration of energy storage systems (ESS) and demand-side flexibility. This enables the SG to not only improve reliability and economic performance but also contribute actively to climate action goals under the United Nations SDGs.

1.3.3. *Optimization method for reliability indicator evaluation*

To assess the impact of solar power uncertainty on SG reliability, this study employs a probabilistic optimization framework to compute key reliability indicators such as LOLP and EENS. These metrics are embedded within a stochastic multi-period optimization model, where power balance, generation constraints and renewable variability are considered under uncertain conditions. The probabilistic model (EENS and LOLP) is applied to predict demand in the case of conventional generation outage. We have extended the problem with emission constraint keeping SDG 12 and SDG 13 perspective in the model, as stated in the optimization methodology.

The objective function is optimized using stochastic programming, which incorporates solar irradiance forecasts modeled through Gaussian distribution and Markov chains. The decision variables include dispatchable generator output *P_gen(t),* storage utilization *P_storage(t)* and slack variables representing unmet demand *P_slack(t).* The optimization seeks to minimize the total system cost while penalizing unreliability as follows:

$$Min\, E\, [\, \sum (C\_gen(t)\; +\; \lambda 1\; *\; LOLP(t)\; +\; \lambda 2\; *\; EENS(t))\,] \qquad [1.11]$$

where:

– λ_1, λ_2 are penalty coefficients;

– $LOLP(t) = Pr(P\_solar(t) + P\_gen(t) + P\_storage(t) < P\_load(t))$;

– $EENS(t) = E[P\_load(t) - P\_supplied(t)]$.

The solution space is explored using scenario-based analysis, where multiple solar generation trajectories are simulated, and the grid’s response is optimized under each scenario. This allows for the quantification of reliability indices under varying irradiance conditions, improving planning and operational decisions. By integrating these indicators directly into the objective function, the optimization ensures that reliability is not just evaluated post-simulation but is actively optimized alongside cost and emissions.

1.3.4. *Mathematical modeling of smart grid components*

1.3.4.1. *Solar PV generation*

The stochastic power output from solar panels is given by:

$$P_{solar(t)} = A \cdot G(t) \cdot \eta \cdot \left[1 - \beta\left(T(t) - T_{ref}\right)\right] \quad [1.12]$$

where:

– A = panel area;

– $G(t)$ = solar irradiance at time t;

– η = panel efficiency;

– β = temperature coefficient;

– $T(t)$ = panel temperature;

– T_ref = reference temperature (usually 25°C).

1.3.4.2. *Conventional generator output*

$$0 \le P\_gen(t) \le P\_gen\_\mathrm{max} \quad [1.13]$$

Subject to ramp-up and ramp-down constraints:

$$P\_gen(t) - P\_gen(t-1)| \le R\_rate \quad [1.14]$$

1.3.4.3. *Energy storage system (battery)*

State of charge (SOC) is given as:

$$SOC(t+1) = SOC(t) + \eta\_ch \cdot P\_ch(t) - P\_dis(t)/\eta\_dis \quad [1.15]$$

Constraints are given as:

$$0 \le SOC(t) \le SOC\_max \quad [1.16]$$

$$0 \le P\_ch(t), P\_dis(t) \le P\_rated \quad [1.17]$$

where:

– η_ch, η_dis = charging/discharging efficiency.

1.3.4.4. *Load demand balance*

Here, we have:

$$P\_solar(t) + P\_gen(t) + P\_dis(t) + P\_slack(t) = P\_load(t) + P_{ch(t)} \quad [1.18]$$

where:

– *P_slack(t):* unmet demand or surplus handling.

1.3.4.5. *Emission model for dispatchable generators*

$$E\_emissions(t) = \varepsilon \cdot P\_gen(t) \quad [1.19]$$

where ε is the emission factor in kg CO_2/kWh.

1.4. Uncertainty in solar power generation

Uncertainty in solar power generation is defined as the unpredictability of the amount of electricity produced by PV systems as a result of factors such as weather, cloud cover, time of day, seasonal changes and geographic location. Solar electricity, unlike conventional power plants, produces variable and intermittent outputs. This unpredictability complicates power system planning, real-time management and maintaining an equilibrium between electricity supply and demand. For example, quick cloud movement can induce significant changes in solar irradiation, resulting in rapid declines in PV system production. In contrast, unexpectedly bright skies can lead to a surplus of generation. These variations have the potential to jeopardize the power grid's reliability and stability, particularly in systems that rely heavily on renewable energy.

To manage these risks, grid operators use forecasting methodologies, energy storage technologies and flexible grid structures like SGs. Forecasting helps predict solar generation using weather data, but forecasts are never precise. As a result, energy storage, such as batteries, is required to store excess energy during peak sunshine and provide it when solar power declines. Furthermore, modern control systems and real-time monitoring allow SGs to respond to shifting generation levels by rerouting power or activating backup generators as needed. From a planning standpoint, integrating solar power under uncertainty necessitates probabilistic modeling and robust optimization to ensure that the grid remains reliable even in worst-case scenarios. Addressing solar power uncertainty is crucial not only for grid dependability, but also for reaching larger sustainability objectives such as carbon neutrality and assisting with the energy transition.

1.5. Real-time monitoring in SGs

Real-time monitoring in the context of SGs and solar power generation is the continuous observation, measurement and analysis of various grid characteristics and energy flows as they occur. It is critical in improving the stability, efficiency and responsiveness of modern electrical grids, particularly those that use intermittent RES such as solar power. Real-time monitoring systems gather information from smart meters, sensors, phasor measuring units (PMUs), weather stations and DERs. These data streams are routed to control centers or cloud-based systems, where powerful algorithms immediately examine them. Solar irradiance, PV panel output, battery charge, voltage levels, frequency variations, power flow across transmission lines and load demand are some of the key characteristics monitored. This continuous view enables operators to detect anomalies, foresee possible concerns and make informed decisions to keep the grid stable.

Real-time monitoring in solar power generation helps to manage oscillations by allowing for dynamic adjustments. For example, if solar production falls unexpectedly owing to cloud cover, the system can swiftly dispatch stored energy or adjust other power sources to compensate. It also aids demand-side management by modifying consumption patterns or employing automatic actions such as turning off non-critical loads. Furthermore, real-time data are critical for defect identification and predictive maintenance, lowering downtime and operational expenses. The integration of IoT devices, edge computing and AI-based analytics has considerably increased the efficacy of real-time monitoring. Together, these technologies provide the situational awareness required to manage a robust, intelligent and sustainable SG in accordance with carbon neutrality and the SDGs.

1.5.1. *Energy generation and solar power tracking*

Real-time monitoring systems measure solar panel output based on current solar irradiance levels, temperature and system efficiency. Because solar power output is highly intermittent, these systems constantly monitor power generation and update projections to account for weather, time of day and seasonal variations. If an unexpected weather condition, such as cloud cover or rain, reduces solar production, real-time data enable grid operators to recognize the change and take immediate corrective action.

1.5.2. *Energy storage systems*

Real-time monitoring of energy SDs, such as batteries or other types of energy storage, is crucial to ensuring that energy is available when it is required. By monitoring the SOC, charge/discharge cycles and health of SDs, grid managers may make informed decisions about when to store extra energy or return it to the grid. Monitoring ensures that storage systems are neither overcharged or discharged above their capacity, which could result in damage or decreased efficiency.

1.5.3. *Grid stability and power flow*

Real-time monitoring is critical for ensuring grid stability, particularly when integrating variable-output RES such as solar. Operators can avoid difficulties like overloads or blackouts by continuously analyzing power flow and voltage levels across the system and redistributing energy as needed. The system may also monitor the performance of DERs such as wind turbines, microgrids and CHP systems, ensuring their seamless integration into the wider grid network.

1.5.4. *Load management and demand response*

Real-time monitoring is an important tool for regulating customer demand. The system uses advanced metering infrastructure (AMI) and smart appliances to track energy consumption patterns and forecast peak load times. Based on this information, grid operators can utilize demand response tactics to alter or reduce energy use during peak periods, such as paying customers to shift energy usage to off-peak hours or automating equipment to minimize load.

1.5.5. *Fault detection and predictive maintenance*

One of the most important advantages of real-time monitoring is early fault detection. By constantly monitoring sensor data for anomalies or departures from normal operation, the system can warn operators of potential equipment failures such as circuit faults, transformer malfunctions or power flow disruptions. Predictive maintenance algorithms can use real-time data to anticipate when equipment will fail and plan maintenance before a problem arises. This proactive approach decreases downtime, lowers operational costs and increases the life of grid assets.

1.5.6. *Data-driven decision-making and dynamic grid management*

Real-time data are fed into advanced control systems, which use dynamic, automated judgments to balance supply and demand. For example, if solar generation is strong during the day, excess energy can be stored in batteries or sent into the grid; however, if generation reduces unexpectedly due to overcast weather, backup power sources can be triggered. Operators can use data visualization dashboards to gain a comprehensive view of grid performance and alter parameters in real-time. Machine learning and AI algorithms can also be used to forecast grid behavior, optimize resource allocation and reduce operating costs.

1.5.7. *Communication and integration of distributed systems*

Real-time monitoring systems are required for communication between various DERs and the main grid. For example, if a solar farm, wind turbine or battery storage system is linked to the grid, it must constantly report its status, power output and any operational changes to the central grid management system. Advanced communication protocols such as DNP3, IEC 61850 and Modbus allow for seamless data transfer between devices and control centers, guaranteeing that all SG components can respond dynamically to changes in real-time.

1.5.8. *Challenges in real-time monitoring*

– *Data overload*: SG technologies create huge amounts of data, which might overwhelm traditional monitoring infrastructure. Efficient data processing, aggregation and filtering procedures are required to derive useful insights from this data. Cloud computing and edge computing are frequently used to process and store real-time data closer to the source, resulting in lower latency and faster decision-making.

– *Cybersecurity*: the risk of cyber-attacks increases as more gadgets and systems connect to the internet. Real-time monitoring systems must use robust encryption and secure communication protocols to protect sensitive data and avoid hostile interference.

– *Integration of diverse technologies*: integrating various technologies and devices, such as traditional power plants, RES and ESS, into a unified real-time monitoring network necessitates the use of a common communication and control architecture. This can be difficult because of the disparate standards and protocols utilized by different systems.

1.5.9. *Benefits of real-time monitoring*

– *Enhanced grid reliability*: real-time monitoring enables operators to respond swiftly to disturbances and avoid outages by providing continuous view into the grid's performance. The grid can be more adaptable and resilient to fluctuations in supply and demand.

– *Optimized resource allocation*: real-time data enable grid operators to optimize the utilization of available resources. For example, solar energy can be used first, followed by stored energy, and conventional electricity can be used last, reducing emissions and operational expenses.

– *Increased efficiency*: continuous monitoring and improvement of power flow results in increased energy efficiency. The technology ensures that just the required quantity of electricity is generated or pulled from storage, reducing waste and improving the grid's overall performance.

– *Supporting sustainability goals*: real-time monitoring facilitates the transition to a sustainable energy future by allowing for more efficient use of renewable energy. It maximizes solar electricity during sunny hours, stores excess energy for later use and maintains system reliability without using fossil fuels.

Real-time monitoring in SGs enables a more dynamic, responsive and resilient power network, especially as solar power and other RES become more prevalent. By integrating advanced sensors, data analytics and automated control systems, real-time monitoring not only ensures grid stability but also supports the long-term goal of carbon neutrality and sustainable energy development.

1.6. Optimization of electricity flow in SGs

The optimization of electricity flow in SGs is crucial to guaranteeing the efficient, reliable and long-term operation of modern power systems. This process entails real-time coordination of energy generation, transmission, distribution and consumption to minimize losses, balance supply and demand, and fully use RES such as solar and wind. Unlike traditional networks, where electricity flows in one direction from centralized power plants to customers, SGs allow for multidirectional power flows, thanks to the integration of DERs. This complexity needs advanced optimization strategies to ensure grid reliability and cost-effectiveness as we work toward carbon neutrality and the SDGs.

1.6.1. *Advanced optimization techniques*

SG optimization uses a variety of advanced methodologies, including optimal power flow (OPF), which determines the most economical generation and distribution patterns while taking into account system restrictions such as voltage limits, power balance and equipment capacity. Stochastic and robust optimization models are increasingly being employed to account for uncertainties in solar irradiance and load demands, hence maintaining system resilience under changing conditions. Another major method is MPC, which regularly adjusts decisions based on short-term generation and demand estimates, making the grid more responsive to changes.

1.6.2. *Energy storage and demand response*

ESS, particularly battery storage, play an important role in managing power flow by absorbing excess solar energy during peak generation and releasing it during times of high demand or low solar output. These solutions reduce curtailment while increasing grid flexibility. Demand response (DR) complements this by adjusting consumer electricity usage in response to price signals or grid needs. Non-critical loads can be shifted to off-peak hours via DR, which contributes to load balancing and reduces the demand for peaking plants powered by fossil fuels.

1.6.3. *Power electronics and smart devices*

The use of power electronics, such as smart inverters and converters, allows for precise control over power quality factors such as voltage, frequency and harmonics. These devices enable solar and other RES to communicate seamlessly with the grid, facilitating bidirectional power flow and grid stabilization. Furthermore, smart appliances and home energy management systems (HEMS) enable users to engage in energy optimization by scheduling usage based on real-time grid circumstances and dynamic pricing.

1.6.4. *Communication technologies and IoT integration*

Optimizing electricity flow also necessitates a strong communication infrastructure powered by IoT technology. Smart meters, phasor measurement units (PMUs) and remote terminal units (RTUs) constantly transmit operational data to central or decentralized control centers. These systems use protocols such as IEC 61850 and DNP3 to enable quick, secure and consistent data flow. These real-time data are critical for adopting adaptive control strategies and coordinating many grid components, such as DERs, microgrids and EV charging stations.

1.6.5. *Energy management systems (EMS)*

EMS are critical to the optimization process because they act as control hubs for assessing data, projecting demand and generation, and allocating energy resources accordingly. EMS platforms use cloud computing and edge analytics to optimize the grid at multiple levels, including generation, transmission, distribution and consumption. They can perform real-time optimization processes to ensure cost-effective operation while meeting technological limits and environmental objectives.

1.6.6. *Benefits and strategic importance*

The optimization of power flow has various advantages, including greater grid reliability, lower operational costs, increased energy efficiency and decreased greenhouse gas emissions. It also encourages the use of intermittent renewables, which accelerates the transition to a low-carbon energy future. As governments work to reach their carbon neutrality targets, electricity flow optimization in SGs becomes a critical component of establishing robust and sustainable energy systems.

1.7. Conclusion

The integration of solar electricity into SGs is critical to meeting the SDGs, particularly carbon neutrality. However, the inherent volatility and intermittent nature of solar irradiation pose severe reliability difficulties. According to the literature review, probabilistic modeling, AI, predictive maintenance, robust optimization, and hybrid transmission systems are critical for managing these uncertainties. To maintain a stable and continuous power supply, studies repeatedly highlight the importance of improved reliability measures such as LOLP and EENS, SG adaptability, and the deployment of storage technologies. Furthermore, replacing coal-based electricity with solar energy considerably cuts carbon emissions, helping to achieve global climate goals. Overall, while solar-integrated SGs have the potential to enable a low-carbon future, the transition's success is dependent on the ability to efficiently and reliably manage uncertainty through new technology and educated regulatory frameworks.

1.8. Policy implications

– *Incentivizing renewable integration*: governments must provide economic and regulatory incentives to encourage the incorporation of solar electricity into smart networks. This covers tax credits, feed-in tariffs and subsidies for both residential and utility-scale solar plants.

– *Investment in grid modernization*: policy frameworks should prioritize investments in grid infrastructure upgrades, such as AMI, battery storage systems and real-time monitoring technologies, to accommodate solar fluctuation.

– *Mandatory reliability standards*: regulatory organizations should develop and enforce reliability criteria that are specifically adapted to renewable-rich systems. These should contain probabilistic performance indicators such as LOLP and EENS to provide proper planning and operational protections.

– *Support for research and innovation*: to increase solar power reliability, governments and international organizations should invest in research and development of new technologies such as AI-driven forecasting, predictive maintenance and robust optimization models.

– *Integrated energy planning*: policymakers should use comprehensive energy planning approaches that match SG development with national carbon neutrality targets, guaranteeing cross-sectoral coordination between the energy, transportation and environmental sectors.

– *Cybersecurity and grid resilience regulation*: policies must need comprehensive cybersecurity frameworks for SG infrastructure to protect against escalating cyber-physical dangers in digitally connected energy systems.

– *International collaboration*: transnational agreements and regional collaboration on grid interconnection can assist in balancing solar variability and increase global energy security. Cross-border solar energy transmission and consistent technological standards are critical in this regard.

– *Public awareness and engagement*: public policy should also prioritize raising knowledge and involvement in demand-side control initiatives, as well as encouraging energy efficiency and responsible solar usage among consumers.

1.9. Future directions

Future research should focus on developing machine learning models to anticipate solar output and grid behavior in real-time under changing weather circumstances.

The integration of long-duration storage technologies, such as battery energy storage systems (BESS), is crucial for reducing solar variability and increasing reliability.

Coordinated policies are necessary to promote investments in renewable infrastructure, grid upgrading and smart meter deployments, particularly in emerging regions. As SGs become more digitalized, effective cybersecurity and reliability measures are needed to address both cyber and physical disruptions. Exploring multi-source energy systems (e.g. solar-wind-battery) and AC-DC hybrid grids can provide greater flexibility and operational reliability. Researching transcontinental solar power networks can balance diurnal solar variations and promote global energy fairness and reliability. Optimizing grid dependability using real-time demand response and decentralized EMS is a potential topic for future investigation.

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