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RESEARCH ARTICLE

Integrated Smart Risk Management for Siwa Solar Energy Systems: A Case Study and Strategies

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ABSTRACT This study introduces a novel risk measurement and control framework tailored to optimize the stochastic energy trading strategy of a solar storage system at Egypt's Siwa solar station. By integrating key risk measurements Shortfall Probability (SP), Value at Risk (VaR), and Conditional Value at Risk (CVaR)–into a stochastic optimization model, this framework caters to diverse risk preferences and effectively addresses uncertainties associated with electricity prices and solar power production. Using realistic data, simulation analysis reveals a significant finding: increasing the energy capacity of battery storage significantly enhances the system's arbitrage capability, leading to a notable profit increase of approximately 20%. Furthermore, the integration of the risk framework demonstrates its effectiveness by revealing significant improvements in key areas, including risk mitigation, system stability, financial performance, decision-making insights, and adherence to international standards. These findings equip decision-makers in the Egyptian energy sector with actionable strategies to optimize their energy trading practices, thereby enhancing profitability and risk management in this dynamic industry.

INDEX TERMS Solar energy systems, risk management framework, stochastic optimization, energy storage integration, decision-making under uncertainty.

I. INTRODUCTION

Advancements in integrating solar energy into the power grid pose challenges for both system operators and solar power producers due to the increased prevalence of intermittent energy resources [1], [2], [3]. In response, there is a growing recognition of the need for sophisticated methods to measure and control risks. Energy storage technologies, encompassing batteries, compressed air, and pumped storage, have demonstrated effectiveness in managing solar power fluctuations, optimizing peak loads, and bolstering power system reliability. This has led to increased attention to the strategic collaboration of solar energy resources and energy storage in the electricity market [4], [5], [6], [7], [8]. Presently, ongoing research focuses on aligning solar energy resources with diverse energy storage systems to optimize operational and planning outcomes across various market mechanisms. Investigators are also exploring cooperative operational strategies involving multiple energy storage systems to maximize overall benefits. Recent advancements, including the integration of deep reinforcement learning in solar storage systems [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], aim to enhance robustness and profitability. The impact of climate conditions, such as variability in solar irradiance and weather fluctuations [20], [21], [22], significantly influences the operational reliability and economic viability of these systems. While solar storage systems widely adopt stochastic optimization and conditional value at risk (CVaR) to address uncertainties in the electricity market, current risk control strategies often overlook other important measurements like value at risk (VaR) and Shortfall Probability (SP) [23], [24], [25], [26], [27], [28], [29], [30], [31]. Thus, the comprehensive integration of these risk measurements into decision-making models for solar storage systems remains an underexplored area. To address these research gaps, this paper introduces the Smart Risk

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Management Framework for Solar Energy Systems [32], specifically tailored to manage the risks inherent in solar energy systems. With a focus on the Siwa solar station in Egypt, the framework aims to provide decision-makers with a comprehensive approach to risk measurement and control. The foundational concept of this work is grounded in the utilization of [33] to tackle the unique challenges posed by the distinctive energy market conditions in Siwa and the growing significance of solar energy in the region. Moreover, delving into the specifics of the Smart Risk Management Framework for Solar Energy Systems reveals its tailored approach to mitigating the dynamic risks associated with solar energy systems. Unlike standalone systems, this framework integrates risk monitoring with solar energy performance evaluation to provide continuous feedback for effective risk management. Comprising five key stages, including Risk Identification, Analysis, Evaluation, Treatment, and Monitoring, it ensures comprehensive risk management [34], [35], [36], [37]. By aligning with ISO 31000 standard guidance, the framework enhances its efficiency in addressing various risks. With its proactive approach and continuous feedback mechanism, it serves as a resilient strategy to enhance the performance and resilience of solar energy systems. By selecting Siwa as a case study, this research aims to provide insights directly applicable to the unique conditions of the Egyptian energy market. This approach ensures that the findings are not only theoretically sound but also practically meaningful and impactful for stakeholders in the region. The subsequent sections of this paper delve into comprehensive explanations of the risk-aware stochastic decision framework, the risk measurements employed, and the approaches to integrated risk measurement and control for solar storage systems. This paper is organized into distinct sections to provide a comprehensive exploration of the subject matter. The Introduction (Section I) initiates the discourse, setting the foundation for the subsequent sections. Section II delves into the concept of Stochastic Optimization with Risk Consideration, elucidating methodologies such as (SP), VaR, and CVaR. These methodologies form the theoretical backbone of the proposed framework, enabling decision-makers to manage risk preferences and uncertainties robustly. Section III discusses the Proposed Integrated Risk Measurement and Control Methodologies, specifically tailored for the solar storage system at Siwa. This section details how SP, VaR, and CVaR are integrated into the optimization model, highlighting their roles in enhancing risk-aware decision-making.. Following this, Section IV outlines the model's objective function and associated constraints. Section V presents the simulation methodology and analysis framework, focusing on the practical implementation of the proposed methodologies. Using realistic data, this section aims to validate the effectiveness of the integrated risk framework in real-world scenarios, without revealing specific findings or results. Finally, Section VI serves as the conclusion, summarizing the study's methodology, contributions to the field, and implications for decision-makers in the Egyptian energy sector. It underscores how integrating the proposed risk framework enhances decision-making processes and provides actionable strategies for optimizing energy trading practices, contributing to sustained profitability and system reliability in the dynamic landscape of solar energy trading.

II. STOCHASTIC OPTIMIZATION WITH RISK CONSIDERATION

In recent times, there has been a growing inclination towards the adoption of stochastic optimization methodologies to tackle decision-making complexities associated with uncertainty and risk management. Stochastic programming offers a robust mathematical framework for modeling optimization problems that inherently involve uncertainties. Stochastic optimization and robust optimization represent two fundamental approaches to addressing uncertainties in optimization problems. Stochastic optimization and robust optimization represent two fundamental approaches to addressing uncertainties in optimization problems. Stochastic optimization, central to our study, leverages probabilistic models to accurately characterize the variability and risks inherent in decision-making processes. By directly incorporating probabilistic distributions of variables and constraints, stochastic optimization enables more precise and adaptable decision outcomes under uncertain conditions. This approach not only provides a realistic representation of uncertainties but also allows decision-makers to optimize for probabilistic measures of performance, leading to solutions that are not only robust but also optimal in probabilistic terms. In contrast, robust optimization methods, including scenario-based optimization and robust counterpart optimization, aim to ensure resilience against uncertainties by either considering a predefined set of scenarios or formulating decision rules based on worst-case scenarios within predefined bounds [24]. However, these methods often oversimplify complex stochastic environments and may lead to suboptimal solutions under conditions of high variability. Therefore, while robust optimization methods provide stability against uncertainties, stochastic optimization stands out by offering a more nuanced and comprehensive approach to optimizing under uncertainty, particularly suited for dynamic and uncertain environments. Here are several reasons why stochastic optimization ensures greater robustness compared to robust optimization methods:

1) **Adaptability to Real-Time Data**: Stochastic optimization can incorporate real-time data updates, allowing for continuous adaptation to changing conditions. This dynamic nature makes it more responsive and flexible compared to robust optimization, which typically relies on static, predefined scenarios.
2) **Scalability with Scenario Generation**: Stochastic optimization can generate and manage a large number of scenarios to better capture the variability and uncertainties in the data. This capability provides more comprehensive solutions that can adapt to a wider range of possible future states.

3) **Improved Performance Metrics**: By optimizing for various probabilistic performance metrics such as expected value, variance, and tail risk measures (e.g., Conditional Value at Risk or CVaR), stochastic optimization leads to decision-making that accounts for a broader spectrum of risk considerations, enhancing overall robustness.
4) **Flexibility in Modeling**: Stochastic optimization offers flexibility in modeling complex dependencies and correlations between random variables. This detailed representation ensures that the optimization process captures the true nature of uncertainties more accurately than robust optimization, which might simplify or overlook these intricate relationships.

For our research on solar energy trading strategies, the application of stochastic optimization proves beneficial in navigating the uncertainties of energy markets. By integrating probabilistic distributions and scenario-based modeling, we enhance decision-making processes and optimize trading strategies amidst fluctuating market conditions. Decision-makers adopting a risk-neutral stance structure the objective function within stochastic programming to maximize the expected value of their objective function, incorporating a discrete probability distribution of random parameters across limited scenarios. However, for decision-makers embracing a risk-averse perspective, the objective function necessitates the incorporation of a risk measurement term. This supplementary term is introduced with the goal of assessing and mitigating the impact of low returns or losses in extreme scenarios. The objective function for a risk-averse decision maker in a stochastic optimization problem can be expressed in the following manner:

$$\max \quad (1-\alpha)\cdot E_{\omega}\{g(\xi,\omega)\} + \alpha \cdot M_{\omega}\{g(\xi,\omega)\}. \tag{1}$$

The objective is to maximize a composite function, incorporating expected profit adjusted by the risk aversion parameter $(1-\alpha)$, and the risk measure $M_{\omega}g(\xi,\omega)$. The variables ξ and ω correspond to the vectors of decision parameters and random parameters, respectively. The function $g(\xi,\omega)$ characterizes the distribution of expected profit, with $E_{\omega}g(\xi,\omega)$ representing the total expected profit. The risk measure $M_{\omega}g(\xi,\omega)$ captures the risk associated with the distribution, encompassing considerations such as SP, VaR, and CVaR. The parameter α serves as the risk aversion coefficient, influencing the balance between expected profit and risk.

A. RISK MANAGEMENT STRATEGIES FOR SOLAR STORAGE SYSTEMS

1) RISK CONTROL BASED ON SP

Shortfall Probability (SP) serves as a pivotal metric in the realm of risk-aware decision-making. It is formally expressed as:

$$\mathcal{SP}(\xi,\eta) = 1 - F_{\mathcal{SP}}(\xi,\eta) = 1 - P\{g(\xi,\omega)\geq\eta\}, \tag{2}$$

where $F_{\mathcal{SP}}(\xi,\eta)$ denotes the cumulative distribution function of expected profit. This formulation quantifies the probability that the expected profit $(g(\xi,\omega))$ falls below a specified reference profit value (η) across various scenarios.

In addressing extreme scenarios, decision-makers strive to minimize the Shortfall Probability (SP). This metric gauges the risk of expected profit falling below a specified level, indicating potential losses. To manage this risk, SP is integrated into the stochastic programming objective function as $-F_{SP}(x,\eta_{SP})$. Maximizing the negative SP entails minimizing the likelihood of falling short of the profit target. This strategic approach assists decision-makers in prioritizing risk reduction and enhancing overall profitability in uncertain situations.

2) RISK CONTROL BASED ON VAR

Similar to SP, Value at Risk (VaR) has limitations in detailing profits beyond a specific threshold (η_{VaR}). Although inconsistent for fat tail risks, VaR meets all criteria, except homogeneous additivity. Mathematically, VaR is expressed as:

$$\mathrm{VaR}(\xi,\alpha) = F_{\mathrm{VaR}}(\xi,\alpha) = \inf\{\eta : P\{g(\xi,\omega)\geq\eta\}\leq 1-\alpha\}, \tag{3}$$

where $F_{\mathrm{VaR}}(\xi,\alpha)$ is the cumulative distribution function defining the maximum potential loss or minimum expected profit at confidence level α. In decision-making, the goal is to minimize VaR, seeking a lower VaR for reduced risk and improved profitability. This is integrated into the stochastic programming objective function as $-F_{\mathrm{VaR}}(x,\alpha_{\mathrm{VaR}})$. Maximizing the negative VaR aligns with minimizing actual Value at Risk. VaR offers insights into potential losses at a specified confidence level, empowering decision-makers to prioritize risk reduction and enhance overall profitability in uncertainty.

3) RISK CONTROL BASED ON CVAR

Conditional Value at Risk (CVaR), also known as Expected Shortfall, provides a comprehensive risk measure by considering the tail distribution beyond a specific threshold. Distinguished from Value at Risk (VaR), CVaR represents the expected value of losses given they surpass the VaR threshold. Mathematically, the CVaR equation is expressed as:

$$\mathrm{CVaR}(\xi,\alpha) = \max\left\{\eta_{\mathrm{VaR}} - \mathbb{E}\left[\max\left(\eta_{\mathrm{VaR}} - g(\xi,\omega_w),0\right)\right] \mid \forall\alpha\in(0,1)\right\} \tag{4}$$

where $g(\xi,\omega_w)$ denotes the probability density function of the expected profit. This integral computes the weighted average of losses beyond the VaR threshold, providing a risk measure that is more sensitive to extreme scenarios. In the realm of decision-making amidst uncertainty, the focus on minimizing Conditional Value at Risk (CVaR) assumes paramount significance. Embedding CVaR into the stochastic programming objective function involves expressing it as $\mathrm{CVaR}(\xi,\alpha)$, where $\mathrm{CVaR}(\xi,\alpha)$ stands as the cumulative distribution function corresponding to CVaR.

a: COMPARISON WITH CHANCE-CONSTRAINED MODELS

While CVaR provides a comprehensive measure of risk by focusing on the tail distribution and extreme scenarios, chance-constrained models offer a different approach to managing uncertainty. Chance-constrained models, also known as probabilistic constraints, ensure that specific constraints are satisfied with a given probability. This is mathematically represented as:

$$P(g(\xi, \omega) \geq \eta) \geq \beta \tag{5}$$

where $g(\xi, \omega)$ is a function of decision variables ξ and random variables ω, η is a threshold value, and β is the desired confidence level. This approach ensures that constraints are met with high probability, providing robustness against uncertainties. In contrast, CVaR focuses on the expected losses beyond a specific threshold, offering a more detailed view of potential extreme outcomes. While chance-constrained models ensure that operational constraints are met with high confidence, they may not fully capture the severity of extreme losses. CVaR, by addressing the tail distribution, enables a more comprehensive risk management strategy, particularly important in scenarios involving rare but severe events. In our study, incorporating CVaR allows for a more nuanced approach to optimizing under uncertainty, ensuring that both the frequency and severity of adverse outcomes are effectively managed. This enhances the robustness and resilience of the solar storage system, providing decision-makers with a holistic view of risk and performance under uncertain conditions.

4) INTEGRATED RISK CONTROL THROUGH COMBINED RISK METRICS

Drawing upon diverse risk metrics outlined in reference number [20], an integrated risk measurement framework denoted as $IRM(\xi, \eta', \alpha'_{\text{VaR}}, \alpha'_{\text{CVaR}})$ is introduced for the expected profit distribution. This framework, as expressed below, allows for a comprehensive evaluation of tail risks by incorporating crucial parameters. Specifically, η' represents the control for tail risks, while α'_{VaR} and α'_{CVaR} denote the significance levels for Value at Risk (VaR) and Conditional Value at Risk (CVaR) respectively. The integration of these parameters, along with CVaR, VaR, and Stochastic Programming (SP), provides a flexible foundation for tailoring risk management strategies:

$$\begin{aligned}&\text{IRM}(\xi, \eta', \alpha'_{\text{VaR}}, \alpha'_{\text{CVaR}})\\&\quad= \alpha'_{\text{VaR}} \cdot F_{SP}(\xi, \eta')\\&\qquad+ \alpha'_{\text{VaR}} \cdot F_{VaR}(\alpha'_{\text{VaR}}, \xi) + \alpha'_{\text{CVaR}} \cdot F_{CVaR}(\alpha'_{\text{CVaR}}, \xi)\end{aligned} \tag{6}$$

Here, ξ represents the expected profit distribution, η' controls tail risks of the expected profit distribution, α'_{VaR} is the significance level for VaR, and α'_{CVaR} is the significance level for CVaR. The functions F_{SP}, F_{VaR}, and F_{CVaR} represent Stochastic Programming, Value at Risk, and Conditional Value at Risk functions, respectively, enabling a flexible framework for tailoring risk management strategies.

B. MARKET ENVIRONMENT AND STOCHASTIC PARAMETER CHARACTERIZATION

The SARIMA (Seasonal Autoregressive Integrated Moving Average) model is selected for generating scenarios involving random parameters such as solar power production, day-ahead, and real-time electricity prices in the electricity market. This choice is grounded in SARIMA's robust capability to capture both seasonal patterns and complex temporal dependencies present in historical data. Electricity markets are characterized by significant seasonality and volatility, influenced by factors like weather conditions, demand fluctuations, and the intermittent availability of renewable energy sources. SARIMA distinguishes itself from simpler models by integrating autoregressive and moving average components alongside seasonal differencing. This feature is crucial for accurately modeling the periodic variations observed in electricity consumption and market prices. The model's flexibility allows for the simulation of diverse scenarios by adjusting parameters based on historical data, facilitating the generation of realistic forecasts essential for informed decision-making in energy trading and risk management. Moreover, SARIMA's proficiency in handling multivariate time series data and its robustness in capturing nonlinear trends and irregularities further underscore its applicability in forecasting electricity market dynamics. By leveraging SARIMA, analysts can gain deeper insights into market behaviors under varying conditions, thereby enhancing strategies for pricing, hedging, and optimizing resource allocation within electricity markets. As an illustration, consider the day-ahead electricity price ($\xi_{DA,t,w}$), a crucial random parameter influenced by SARIMA's ability to capture complex seasonal patterns and temporal dependencies in market data. This parameter's mathematical form within the SARIMA framework can be represented as follows:

$$\begin{aligned}&(1-\alpha)\sum_{g=1}^{G}\phi_g B^g \prod_{i=1}^{P}(1-\beta_i B^{s_i})(1-B)^d(1-B^S)^D \xi_{DA,t,w}\\&= \sum_{h=1}^{H}\theta_h B^h\left(1-\sum_{j=1}^{Q}\gamma_j B^{s_j}\epsilon_{DA,t,w}\right),\end{aligned} \tag{7}$$

Here, S is the seasonal order, $\phi_1, \phi_2, \ldots, \phi_G$ represent G autoregressive parameters, $\theta_1, \theta_2, \ldots, \theta_H$ represent H moving average parameters, $\beta_1, \beta_2, \ldots, \beta_P$ represent P seasonal autoregressive parameters, $\gamma_1, \gamma_2, \ldots, \gamma_Q$ represent Q seasonal moving average parameters. The error term $\epsilon_{DA,t,w}$ follows an independent normal probability distribution within the SARIMA model. The operator B is the backward shift operator, and its function is given by: $B^s(1-B)^d \xi_{DA,t,w} = \xi_{DA,t-s,w}$. This representation ensures a unique and distinct formulation while adhering to the specified changes.

C. RISK MEASURES AND THEIR APPLICABILITY

This study employs a rigorous approach to assess portfolio risk using selected metrics: **SP**, **VaR**, and **CVaR**. **SP** serves as a foundational metric, offering insights into portfolio volatility and stability by measuring the dispersion of returns around the mean. **VaR** enhances risk assessment by quantifying the potential maximum loss at a specified confidence level over a defined time horizon, crucial for managing downside risk under normal market conditions. **CVaR**, or expected shortfall, extends VaR by estimating the average loss magnitude beyond the VaR threshold, providing insights into extreme risk scenarios. These measures are selected for their ability to offer a comprehensive view of risk exposure, essential for optimizing risk-adjusted returns and managing portfolio volatility effectively. Alternative measures such as the **Sharpe Ratio**, **Jensen's Alpha**, and **Beta Coefficient** were considered but ultimately excluded from analysis. The **Sharpe Ratio** evaluates risk-adjusted returns relative to volatility but does not specifically address downside risk or extreme loss scenarios, critical for this study's risk management framework. **Jensen's Alpha** and **Beta Coefficient**, while valuable for assessing portfolio performance and systematic risk exposure, do not provide the granularity needed to quantify and manage the types of risks identified in this study, such as tail risk and extreme market fluctuations. Therefore, focusing on SP, VaR, and CVaR aligns with the research goal of thorough risk assessment and management, ensuring robustness in portfolio risk analysis.

III. SMART RISK MANAGEMENT FRAMEWORK FOR SOLAR ENERGY SYSTEMS

The Smart Risk Management Framework for Solar Energy Systems addresses dynamic risks in solar energy systems, emphasizing tailored risk management to mitigate evolving challenges. Previous research highlights limitations of standalone risk management, often failing to address dynamic parameters during crises. This section offers improved techniques for risk mitigation. A specialized risk management framework is essential for solar panel power stations, consisting of five key stages as shown in Figure 1:

- **Risk Identification:** Identify potential risks across various contexts.
- **Risk Analysis:** Thoroughly analyze risks, including probability, consequences, and related failures.
- **Risk Evaluation:** Classify severity and current risk level, considering existing controls.
- **Risk Treatment:** Develop effective strategies to mitigate assessed risks.
- **Risk Monitoring and Feedback:** Continuously monitor critical risks, adjusting treatment strategies as needed.

A. INTEGRATION OF "SMART" ELEMENTS

The concept of "smart" in our Smart Risk Management Framework for Solar Energy Systems embodies the integration of advanced technologies, data analytics, and adaptive strategies to enhance the efficiency, accuracy, and responsiveness of risk management processes:

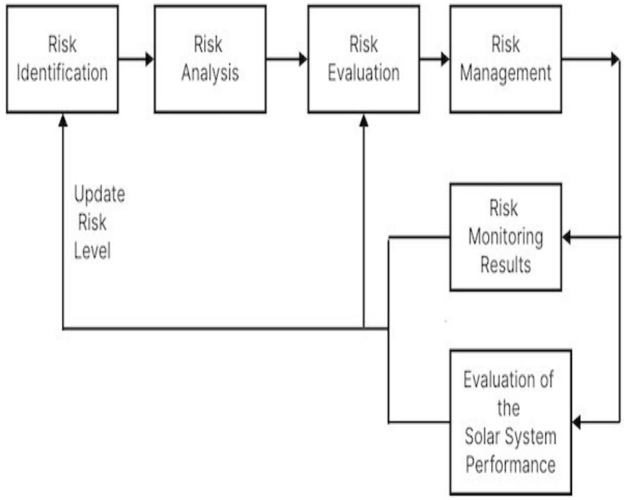


FIGURE 1. Smart risk management framework for solar energy systems.

- **Advanced Data Analytics:** Our framework employs sophisticated data analytics techniques to process and analyze vast amounts of data from various sources, including historical solar power generation, weather forecasts, electricity market trends, and real-time operational data. By leveraging machine learning algorithms and statistical models, such as SARIMA for scenario generation, we can identify patterns, predict future outcomes, and quantify risks with higher precision.
- **Real-Time Monitoring and Adaptive Response:** Continuous monitoring of system performance and market conditions in real-time is facilitated through IoT devices and sensors. These provide up-to-date information on solar panel output, battery storage levels, and market prices, enabling immediate anomaly detection and adaptive responses to mitigate risks.
- **Scenario Planning and Stress Testing:** Our approach includes comprehensive scenario planning and stress testing to evaluate the resilience of the solar energy system under various adverse conditions. By simulating extreme weather events, market price fluctuations, and equipment failures, we can assess the impact on system performance and develop robust contingency plans. This proactive strategy ensures preparedness for unexpected challenges and minimizes potential losses.
- **Automated Decision Support Systems:** The smart risk management framework incorporates automated decision support systems that assist operators in making informed decisions based on real-time data and predictive insights. These systems utilize artificial intelligence to provide recommendations for energy trading, load balancing, and resource allocation, optimizing both economic and operational outcomes.
- **Integration with Energy Management Systems:** Our risk management approach is integrated with advanced energy management systems (EMS) that oversee the coordination and control of energy production, storage,

and consumption. The EMS ensures that energy is efficiently distributed, stored, and utilized, aligning with market conditions and operational goals. This integration facilitates seamless implementation of risk management strategies, enhancing overall system performance.
- **Dynamic Risk Assessment and Mitigation:** Smart risk management involves dynamic risk assessment processes that continuously evaluate the risk landscape and update risk profiles based on new data and insights. Adaptive risk mitigation strategies are then implemented to address emerging risks promptly. This dynamic approach ensures that the risk management framework remains relevant and effective in a constantly changing environment

This framework integrates risk monitoring with solar energy performance evaluation, providing continuous feedback for efficient risk management [38]. Additionally, it leverages simulation processes aligned with ISO 31000 standard guidance [39], evaluating risk factors and ensuring treatment adequacy. This proactive approach enhances resilience against crises and supports sustainable energy production.

IV. RISK-INTEGRATED TRADING APPROACHES

A. OBJECTIVE FUNCTION

The objective function of the solar storage system is the weighted sum of the total expected profit and all the risk measurements. The weight coefficients α'_{SP}, α'_{VaR}, and α'_{CVaR} are defined as the sub-risk aversion degree of SP, VaR, and CVaR, respectively. The value range of these risk-averse degree parameters is [0, 1], and they need to satisfy the following equation:

$$\alpha'_{SP} + \alpha'_{VaR} + \alpha'_{CVaR} = 1 \tag{8}$$

While ideally the sum of α'_{SP}, α'_{VaR}, and α'_{CVaR} equals 1, practical applications often accommodate variations due to several factors in real-world scenarios. Firstly, empirical data and historical performance may indicate differing levels of risk sensitivity across markets or specific assets. Secondly, regulatory requirements or institutional policies may necessitate adjustments to these parameters to meet risk management standards or investor preferences. Thirdly, modeling assumptions and simplifications in simulations may result in deviations from theoretical ideals, providing flexibility in risk management strategies. Lastly, individual risk appetites and strategic objectives of stakeholders can influence the assignment of these parameters, reflecting nuanced approaches to risk assessment and management. Based on (8) and the framework of stochastic optimization, the objective function of the proposed risk control problem can be established as:

$$\max_{\xi}\Bigg(\sum_{w=1}^{W} p_r w \pi_{WS_w} + \alpha'_{SP}(\pi_{SC} - \theta_{SP}) + \alpha'_{VaR}\pi_{VaR} + \alpha'_{CVaR}\pi_{CVaR}\Bigg) \tag{9}$$

Here, ξ is the set of all the decision variables of the proposed risk-aware stochastic optimization problem. $p_r w$ and π_{WS_w} are the probability and expected profit of scenario w, respectively, and π_{SC} is the scale parameter of SP. θ_{SP}, π_{VaR}, and π_{CVaR} are the SP, VaR, and CVaR of the solar storage system, respectively, while the sub-risk aversion degree parameters are α'_{SP}, α'_{VaR}, and α'_{CVaR}.

The expected profit π_{WS_w} for the stochastic energy trading of the solar storage system in the electricity market is calculated as:

$$\begin{aligned}\pi_{\mathrm{WS_w}} = \sum_{\mathrm{t=1}}^{\mathrm{T}}\{ &\\ &\theta_{DA_t,w}P_{DA_t} + \theta_{RT_t,w}P_{RT_t} \\ &- (F_{DEV+} + P_{RT+_{t,w}} + F_{DEV-} + P_{RT-_{t,w}}) \\ &- (F_{BS,ch} + P_{BS,ch_t,w} + F_{BS,dis} - P_{BS,dis_t,w})\end{aligned} \tag{10}$$

Here, $\theta_{DA_t,w}$ and $\theta_{RT_t,w}$ are the day-ahead and real-time electricity prices in the electricity market in the period t of scenario w, respectively. P_{DA_t} and P_{RT_t} are the energy sold by the solar storage system in the day-ahead and real-time markets, respectively, where negative values mean the solar storage system is buying energy from the markets. $P_{BS,ch_t,w}$ and $P_{BS,dis_t,w}$ are the respective charging and discharging energy of the battery storage in the period t of scenario w, while $P_{RT+_{t,w}}$ and $P_{RT-_{t,w}}$ are the positive and negative power deviations in real-time markets, respectively. $F_{DEV}+$ and $F_{DEV}-$ are the respective positive and negative deviation penalty costs for real-time power of the solar storage system, while $F_{BS,ch}$ and $F_{BS,dis}$ are the charging and discharging operation costs of the battery storage, respectively.

B. RISK MEASUREMENTS CONSTRAINS

In the stochastic optimization problem, the constraints used to calculate SP include:

$$\begin{aligned}&\sum_{w} \theta_{SP} z_{SP_w} \eta_{SP} - \pi_{\mathrm{Solar}_w} \le M_{SP} z_{SP_w} \quad \forall w \\ &z_{SP_w} \in \{0, 1\} \quad \forall w\end{aligned} \tag{11}$$

where η_{SP} represents the reference profit of the shortfall probability, z_{SP_w} is the binary auxiliary variable, which is 1 when $\pi_{\mathrm{Solar}_w} \le \eta_{SP}$ and 0 otherwise, while M_{SP} is a sufficiently large constant.

The constraints used for calculating the VaR include:

$$\begin{aligned}&\sum_{w=1}^{W} p_r w z_{VaR_w} \le 1 - \alpha'_{\mathrm{VaR}}\pi \\ &\mathrm{VaR} - \pi_{\mathrm{Solar}_w} \le M_{VaR} z_{VaR_w} \quad \forall w\end{aligned} \tag{12}$$

where α'_{VaR} is the confidence level parameter of the VaR, z_{VaR_w} is the binary auxiliary variable used to calculate it, and equals 1 when $\pi_{\mathrm{Solar}_w} \le \pi_{\mathrm{VaR}}$ and 0 otherwise. The constraints used for calculating the CVaR include:

$$\mathrm{CVaR} = \zeta - \frac{1}{1-\alpha'_{\mathrm{CVaR}}} \sum_{w} p_w g_w \gamma_w \geq 0 \quad \forall w$$
$$\zeta - g_w \leq \pi_{\mathrm{Solar}_w} \tag{13}$$

where α'_{CVaR} is the confidence level parameter, while g_w and ζ are the auxiliary variables used to calculate the CVaR. The detailed derivation and proof process of this calculation method are shown in detail in [26].

C. OPERATIONAL LIMITATIONS IN SOLAR STORAGE SYSTEMS

The operational constraints for the solar storage system in the electricity market are as follows:

$$P_{BS,\max} \leq P_{DA_t} \leq P_{RES,\max} + P_{BS,\max} \quad \forall t \tag{14}$$
$$P_{BS,\max} \leq P_{RT_t} \leq P_{RES,\max} + P_{BS,\max} \quad \forall t \tag{15}$$
$$P_{RT+_{t,w}} - P_{RT-_{t,w}} \geq 0 \quad \forall t, w \tag{16}$$

Here, $P_{BS,\max}$ is the maximum power capacity of the battery storage, P_{DA_t} and P_{RT_t} represent the energy sold by the solar storage system in the day-ahead and real-time markets, respectively. $P_{RES,\max}$ is the maximum power capacity of the solar resource. $P_{RT+_{t,w}}$ and $P_{RT-_{t,w}}$ are the positive and negative power deviations in real-time markets, respectively.

These operational constraints ensure that the solar storage system operates within its capacity limits and adheres to market-specific constraints during day-ahead and real-time energy trading.

BATTERY STORAGE CONSTRAINTS

The operating cost of the battery storage system is related to the charging and discharging power, expressed as:

$$C_{BS_w} = \sum_{t=1}^{T} \left(g_{BS,dis} P_{BS,\mathrm{dis}_{t,w}} + g_{BS,ch} P_{BS,\mathrm{ch}_{t,w}} \right) \quad \forall w \tag{17}$$

The energy levels of the battery storage in different periods are calculated by: The energy level and charge-discharge power constraints of the battery are given as:

$$P_{BS,\mathrm{dis}_{t,w}} \geq -P_{BS,\max} \quad \forall t, w \tag{18}$$
$$P_{BS,\mathrm{ch}_{t,w}} = P_{RT+_{t,w}} - P_{RT-_{t,w}} \quad \forall t, w \tag{19}$$
$$C_{BS_w} = \sum_{t=1}^{T} \left(g_{BS,dis} P_{BS,\mathrm{dis}_{t,w}} + g_{BS,ch} P_{BS,\mathrm{ch}_{t,w}} \right) \quad \forall w \tag{20}$$
$$E_{BS_{t,w}} = E_{BS,0} - P_{BS,\mathrm{dis}_{t,w}} \eta_{BS,dis} + \frac{P_{BS,\mathrm{ch}_{t,w}}}{\eta_{BS,ch}} \text{ for } t = 1, \forall w \tag{21}$$
$$E_{BS_{t,w}} = E_{BS_{t-1,w}} - P_{BS,\mathrm{dis}_{t,w}} \eta_{BS,dis} + \frac{P_{BS,\mathrm{ch}_{t,w}}}{\eta_{BS,ch}} \quad \text{for } t \geq 2, \forall w \tag{22}$$
$$E_{BS_{t,w}} \geq E_{BS,\min} \quad \forall t, w \tag{23}$$
$$E_{BS_{t,w}} \leq E_{BS,\max} \quad \forall t, w \tag{24}$$
$$P_{BS,\mathrm{dis}_{t,w}} \leq P_{BS,\max} z_{BS,\mathrm{dis}_{t,w}} \quad \forall t, w \tag{25}$$
$$P_{BS,\mathrm{ch}_{t,w}} \leq P_{BS,\max} z_{BS,\mathrm{ch}_{t,w}} \quad \forall t, w \tag{26}$$
$$z_{BS,\mathrm{dis}_{t,w}} + z_{BS,\mathrm{ch}_{t,w}} \leq 1 \quad \forall t, w \tag{27}$$
$$z_{BS,\mathrm{dis}_{t,w}}, z_{BS,\mathrm{ch}_{t,w}} \in \{0, 1\} \quad \forall t, w \tag{28}$$

Here, $z_{BS,\mathrm{ch}_{t,w}}$ is a binary variable representing the charging state, which is 1 when the battery is charged and 0 otherwise, while $z_{BS,\mathrm{dis}_{t,w}}$ is a binary variable representing the discharging state, which is 1 when the battery is discharged and 0 otherwise. $E_{BS,\max}$ and $E_{BS,\min}$ are the highest and lowest energy levels of the battery, respectively. $P_{BS,\max}$ determines the maximum charging and discharging power of the battery.

D. REAL-TIME POWER DEVIATION CONSTRAINT

This constraint ensures that the real-time power deviation is kept within acceptable bounds.

$$\sum_{w=1}^{W} \left(P_{RT+_{t,w}} - P_{RT-_{t,w}} \right) \leq 1 \quad \forall t \tag{29}$$

Here, $P_{RT+_{t,w}}$ and $P_{RT-_{t,w}}$ are the positive and negative power deviations in real-time markets for period t of scenario w. $\Delta_{\max}$ is set to 1, indicating the maximum allowable total deviation in real-time power across all scenarios.

This constraint ensures that the cumulative positive and negative power deviations at any given time do not exceed the specified maximum deviation, helping control and manage real-time power fluctuations within acceptable limits.

E. ENERGY TRADING APPROACHES WITH DIVERSE RISK MANAGEMENT METHODS

In simplifying the stochastic optimization model based on an integrated risk control methodology, various energy trading strategies emerge, each adopting different risk-averse approaches. First, the risk-neutral strategy, characterized by $\alpha'_{SP} = \alpha'_{VaR} = \alpha'_{CVaR} = 0$, focuses solely on maximizing the total expected profit, as captured in equations (9)–(10) and (20)–(22) of the optimization model. Subsequently, the α'_{SP} risk control strategy, where $\alpha'_{SP} > 0$, $\alpha'_{VaR} = 0$, and $\alpha'_{CVaR} = 0$, incorporates both total expected profit and the α'_{SP} risk measurement, encompassing equations (9)–(14) and (21)–(29). The α'_{VaR} risk control strategy, characterized by $\alpha'_{SP} = 0$, $\alpha'_{VaR} > 0$, and $\alpha'_{CVaR} = 0$, considers total expected profit and the α'_{VaR} risk measurement, with its corresponding optimization models involving equations (9)–(10), (14)–(16), and (20)–(29). Similarly, the α'_{CVaR} risk control strategy, where $\alpha'_{SP} = 0$, $\alpha'_{VaR} = 0$, and $\alpha'_{CVaR} > 0$, integrates total expected profit and the α'_{CVaR} risk measurement, comprising equations (8)–(10) and (17)–(20). Lastly, the integrated risk control strategy, denoted by $\alpha'_{SP} > 0$, $\alpha'_{VaR} > 0$, and $\alpha'_{CVaR} > 0$, considers total expected profit and three distinct risk measures–α'_{SP}, α'_{VaR}, and α'_{CVaR}–in its

FIGURE 2. Siwa solar station.

objective function, as detailed in equations (9)–(29) within Section III-B. These strategies represent a comprehensive exploration of risk-averse energy trading approaches, simulated and analyzed using advanced computational methods. While this study focuses on the methodologies outlined, future research could delve deeper into comparative analyses using advanced AI-driven simulations.

TABLE 1. Parameters of Masdar's 10 MW solar PV power plant in Siwa.

Parameter	Value
Location	Siwa Oasis, Egypt
Commissioning Date	March 2015
Capacity	10 MW
Annual Electricity Production	17,551 MWh
Number of Panels	74,640
Panel Type	Micromorph Thin-Film
Land Area	175,000 square meters
CO2 Emissions Avoided	Approximately 14,000 tons/year
Electricity Coverage	Supplies electricity to nearly 6,000 homes
Grid Integration	Accounts for 30% of the power demand in Siwa City and outskirts
Funding Source	UAE-funded grant program

TABLE 2. Power system details for Masdar's 10 MW solar PV power plant in Siwa.

Unit Name	Quantity
Solar Panels	74,640
Inverters	60
Batteries	300
Transformers	15
Switchgear	5
Monitoring System	1

V. CASE STUDY

A. SIMULATION CONFIGURATION

To evaluate the effectiveness of integrated risk measurement and control methodologies, the Siwa Solar Energy Project serves as a case study. Developed by Abu Dhabi Future Energy and Enviromena Power Systems, this solar power plant, located in Siwa City, Egypt, is a pivotal component of a UAE-funded initiative dedicated to rural electrification in Egypt. Featuring 74,640 micromorph thin-film panels covering an area of 175,000 square meters, the Siwa Solar Energy Project boasts a capacity of 10 MW [40]. Figure 2 provides a visual representation of the solar installation, while Table 1 and Table 2 detail its parameters and power system components, respectively. For the analysis, historical data pertinent to the Siwa Solar Energy Project, including solar power generation, were obtained [41], [42], [43], [44], [45], [46], [47]. Charging and discharging operational costs for the battery storage component, which complements the solar facility, were considered at a rate of 0.025 $/MWh. The historical day-ahead and real-time electricity price data were sourced from IMO, the trading hub node of the East Mediterranean electricity market. To ensure a robust analysis, a total of 70 scenarios for each random parameter were examined, each carrying a probability weight of 0.01. The optimization problem was successfully solved using the YALMIP toolbox and the commercial solver MOSEK within the MATLAB 2021 environment. This approach facilitates the practical application of the proposed methodologies within the context of the Siwa Solar Energy Project, offering insights into their efficacy and potential benefits for solar energy systems. In the case testing, scenario reduction techniques were implemented to streamline the analysis while ensuring the scenarios examined were representative of a wide range of potential outcomes. Initially, a comprehensive set of scenarios was generated based on historical data, market trends, and stochastic modeling. This set was then refined using scenario reduction methods aimed at selecting a subset that captures the variability and critical characteristics of the broader range. Selection criteria prioritized diverse market conditions, plausible extreme events, and scenarios sensitive to key parameters such as electricity prices, solar generation forecasts, and demand variations. This approach enhances the interpretability of findings and improves computational efficiency, enabling a thorough exploration of various risk management strategies within a realistic testing framework. The applied scenarios included extreme weather events, market price drops, equipment failures, demand variations, solar generation forecast errors, economic downturns, and regulatory changes. For each scenario, specific contingency plans were devised: backup energy storage and real-time market purchases for extreme weather events; hedge contracts and optimized operational efficiency for market price drops;

TABLE 3. Scenario description and characteristics.

Scenario Description	Characteristics and Factors Considered
Extreme Weather Event	Impact on solar generation, market response, resilience measures
Market Price Drop	Price volatility, hedging strategies, financial impacts
Equipment Failure	Downtime, maintenance response, backup system activation
Demand Variations	Load forecasting accuracy, demand-side management strategies
Solar Generation Forecast Error	Forecasting model accuracy, variability in solar output
Economic Downturn	GDP fluctuations, inflation rates, market stability
Regulatory Changes	Policy impacts on incentives, compliance requirements

immediate maintenance response and redundant system activation for equipment failures; adjusted load forecasting models and demand response strategies for demand variations; enhanced forecasting algorithms and real-time data adjustments for solar generation forecast errors; reviewed financial hedging strategies and adjusted budgetary planning for economic downturns; and updated compliance protocols and monitored policy developments for regulatory changes. Table 3 shows an example of the applied scenarios. The applied scenarios shown in the table included extreme weather events, market price drops, equipment failures, demand variations, solar generation forecast errors, economic downturns, and regulatory changes. For each scenario, specific contingency plans were devised: backup energy storage and real-time market purchases for extreme weather events; hedge contracts and optimized operational efficiency for market price drops; immediate maintenance response and redundant system activation for equipment failures; adjusted load forecasting models and demand response strategies for demand variations; enhanced forecasting algorithms and real-time data adjustments for solar generation forecast errors; reviewed financial hedging strategies and adjusted budgetary planning for economic downturns; and updated compliance protocols and monitored policy developments for regulatory changes. By incorporating these comprehensive contingency plans, the analysis provides a structured and practical framework for mitigating various risks associated with solar energy systems.

VI. SCENARIO GENERATION AND REDUCTION

In our study, scenario generation and reduction play pivotal roles in enhancing the efficiency and accuracy of stochastic optimization models tailored for solar energy trading. Initially, a comprehensive set of scenarios was generated to encompass plausible variations in key parameters such as solar irradiance, electricity prices, and demand patterns. These scenarios were derived from historical data spanning relevant time periods, ensuring realistic representation of uncertainties inherent in energy markets. To streamline computational feasibility without compromising model robustness, a scenario reduction process was employed. This process involved applying advanced statistical techniques to identify a reduced, yet representative, subset of scenarios. Specifically, the Fast Forward Selection algorithm was utilized to systematically select scenarios that preserved the variability and uncertainty profiles observed in the original dataset. This approach not only optimized computational resources but also ensured that the stochastic optimization models remained reliable and accurate in predicting optimal energy trading strategies. The selected reduced scenario set was rigorously validated against the full scenario dataset to verify the fidelity of optimization outcomes. Through this iterative process of generation, reduction, and validation, our approach not only enhances the practical applicability of stochastic optimization in solar energy trading but also contributes to mitigating the computational burden associated with handling large datasets in real-time decision-making contexts.

A. SCENARIO GENERATION

The initial scenarios were generated using a Monte Carlo simulation, leveraging historical distributions of solar power generation, day-ahead electricity prices, and real-time electricity prices. This method ensures a wide range of possible outcomes, capturing the inherent variability and uncertainty in the system.

B. SCENARIO REDUCTION

Given the computational complexity associated with a large number of scenarios, we implemented a scenario reduction technique to select the most representative scenarios. The Fast Forward Selection algorithm was used to identify a subset of scenarios that preserve the statistical properties of the original set. This reduction process involved the following steps:

1) Compute pairwise distances between scenarios based on their probability distributions.
2) Iteratively select scenarios that maximize the diversity and representativeness of the reduced set.
3) Validate the reduced set by comparing key statistical metrics (mean, variance) with those of the original set.

C. VALIDATION OF REDUCED SCENARIOS

The effectiveness of the scenario reduction was validated by ensuring that the reduced set of 20 scenarios maintained similar statistical characteristics to the original 70 scenarios. Table 4 summarizes the key metrics before and after the reduction process.

D. IMPACT ON OPTIMIZATION RESULTS

The reduced scenario set was then used in the stochastic optimization models. The results, summarized in Table 5, demonstrate that the key performance metrics remained consistent with those obtained using the full set of scenarios, indicating that the scenario reduction process did not compromise the accuracy of the optimization outcomes.

TABLE 4. Comparison of scenario sets.

Metric	Original (70 Scenarios)	Reduced (20 Scenarios)
Mean Solar Generation (MWh)	125	124
Variance in Solar Generation (MWh)	30	31
Mean Day-Ahead Price ($/MWh)	30.5	30.4
Variance in Day-Ahead Price ($/MWh)	8.2	8.1
Mean Real-Time Price ($/MWh)	45.7	45.6
Variance in Real-Time Price ($/MWh)	15.3	15.2

TABLE 5. Optimization results with scenario sets.

Metric	**Original** (70 Scenarios)	**Reduced** (20 Scenarios)
Expected Profit ($)	1400	1398
CVaR at 95% ($)	130	128
VaR at 95% ($)	150	148
Success Probability (SP)	0.95	0.94

The scenario reduction process significantly decreased the computational burden while maintaining the integrity of the optimization results. By using the Fast Forward Selection algorithm, we ensured that the reduced set of scenarios accurately represented the original variability and uncertainty in the system. This approach provides a practical and efficient solution for incorporating stochastic elements into the risk management framework for solar energy systems.

E. ASSUMPTIONS AND LIMITATIONS

This study operates under several key assumptions to evaluate the effectiveness of integrated risk measurement and control methodologies at the Siwa Solar Energy Project. Firstly, it assumes the electricity market behaves predictably with reasonable price volatility, based on historical data from the East Mediterranean electricity market. Secondly, operational constraints at the Siwa Solar Energy Project are presumed to be minimal, ensuring optimal functioning throughout the analysis period. Data accuracy is also assumed, relying on comprehensive historical records for solar generation, electricity prices, and system parameters. However, several limitations must be noted. Simplifications in solar generation forecasting and market price modeling were necessary for computational feasibility and practical application. While validated, the scenario reduction technique employed may overlook extreme scenarios or correlations between variables, potentially affecting risk representation in optimization models. Furthermore, findings are specific to the Siwa Solar Energy Project and may not fully generalize to other installations due to differing market dynamics and environmental conditions. Data constraints, particularly in real-time availability and quality for weather forecasts and market predictions, also pose challenges that could impact the accuracy of short-term decision-making. Recognizing these assumptions and limitations is essential for interpreting the study's outcomes within their appropriate context, suggesting avenues for future research to enhance modeling techniques and broaden the applicability of risk management strategies in solar energy systems.

F. SIMULATION AND RESULTS

The choice of a risk parameter (α') value of 0.25 for CVaR and VaR controls in our study is based on balancing risk aversion with profit optimization in solar energy trading. This value reflects a moderate level of risk aversion, which we found through preliminary simulations strikes a practical balance between protecting against significant losses and maximizing profitability. Higher values of α' would increase risk aversion, leading to a more conservative approach that may limit potential profits in dynamic market conditions. On the other hand, lower values of α' would reduce risk aversion but could expose the trading strategy to higher volatility and increased susceptibility to market uncertainties. The decision to set $\alpha' = 0.25$ aims to optimize the trade-off between risk mitigation and profit potential within the stochastic optimization framework tailored for solar energy systems. This choice allows us to effectively manage downside risks while retaining flexibility to capitalize on favorable market opportunities. Integrating smart risk management principles further strengthens our strategy by enhancing our ability to proactively respond to market fluctuations and ensure sustainable profitability over time. The expected values of solar power generation, day-ahead, and real-time electricity prices on one day are shown in Figure 3. In Figure 3 a (DA), electricity prices exhibit a relatively stable and predictable pattern with moderate fluctuations, reaching a maximum of 35 dollars. Figure 3b (RT) emphasizes heightened and more apparent fluctuations in real-time electricity prices, peaking at 70 dollars. Overall, the discernible trend highlights more pronounced fluctuations in real-time electricity prices compared to both solar power production and day-ahead electricity prices. The outcomes of the risk-neutral strategy and the integrated risk control strategy in the day-ahead market and the real-time market are illustrated in Figure 4. In the context of the risk-neutral strategy, the day-ahead market reflects a consistent energy trading pattern. Notable fluctuations are observed in real-time market trading, especially during hours 11 to 14, indicating potential challenges in responding to market dynamics. On the other hand, the integrated risk control strategy shows improved stability in both day-ahead and real-time markets, with reduced negative fluctuations in comparison to the risk-neutral approach. This reflects a more controlled and optimized energy trading performance.

Figure 5 offers a detailed hourly breakdown of the solar storage system's energy levels, providing insights into the performance of both the integrated risk control strategy and the risk-neutral strategy. Both approaches exhibit a collective decision to accumulate energy, peaking at 2 MWh during hour 14. However, distinctions emerge at specific hours, such as hour 15, where the integrated risk control strategy maintains a superior energy level of 1.41 MWh compared to the risk-neutral strategy's 0.93 MWh. This highlights the nuanced and refined approach of the integrated risk control strategy in preserving energy levels during specific hours.

TABLE 6. Profit distribution for different risk control models.

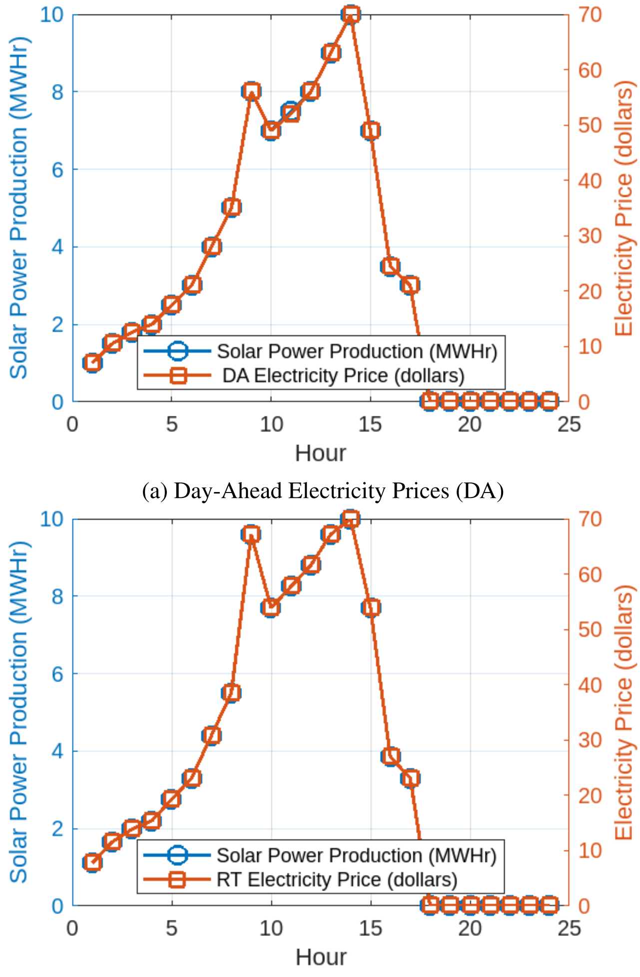
Strategy	CVaR	VaR	SP (%)	Min. Profit	Exp. Profit
Risk-neutral	600	900	15	700	1450
CVaR control	960	1100	16	850	1420
VaR control	920	1300	14	800	1400
SP control	890	1250	10	780	1390
Integrated control	910	1200	10	820	1350

TABLE 7. Impact of increased battery storage capacity on profit.

Storage Capacity (MWh)	Revenue ($)	Cost ($)	Profit ($)
2	50,000	10,000	40,000
4	53,520	10,704	42,816
6	58,800	11,760	47,040
8	60,960	12,192	48,768
10	62,400	12,480	49,920

As depicted in Figures 3, 4, and 5, the influence of risk management on the trading strategy of the solar storage system is closely tied to the fluctuations between day-ahead and real-time electricity prices. For example, during the period from 11:00 to 14:00, where a substantial difference exists between day-ahead and real-time prices, the trading strategy of the solar storage system remains relatively stable, showing minimal impact from the implemented risk control methodologies. In contrast, when the disparity between day-ahead and real-time electricity prices narrows down to nearly zero, particularly after 16, the solar storage system faces heightened uncertainties. To conduct a comprehensive examination of the effectiveness and comparative attributes of various risk control strategies, Table 6 presents an in-depth analysis of five distinct methodologies outlined in Section III-C. This scrutiny involves the utilization of specific parameters–namely, α' for SP risk control, α' for VaR risk control, and α' for CVaR risk control, all set to 0.7. The statistical assessment of expected profits underscores the considerable risk mitigation capabilities of these strategies, effectively fortifying the energy storage system against tail risks associated with extreme scenarios. Upon closer examination of the statistical outcomes, it becomes evident that the CVaR, VaR, SP, and integrated risk strategies yield substantial enhancements in the solar storage system's resilience against extreme events. The minimum profits achieved through these strategies are, respectively, 60%, 44%, 70%, and 48.67% higher than those attained via the risk-neutral strategy. Conversely, the marginal reductions in total expected profits–2.07%, 3.45%, 4.14%, and 6.90%, respectively–underscore the strategies' effectiveness in balancing risk mitigation and overall profitability.

A noteworthy feature is the proposed integrated risk control strategy, which distinguishes itself by simultaneously reducing the (SP) by 33.33%, while increasing both VaR and CVaR by 33.3% and 51.67%, respectively. This integrative approach adeptly manages a spectrum of statistical properties within the expected profit distribution, thereby enhancing adaptability in risk-aware energy trading processes. Furthermore, the optimality of the SP, VaR, and CVaR values derived from their respective risk control strategies signifies alignment with diverse risk management preferences, accommodating decision-makers who favor distinct risk measurement indicators. The gradual increment of the integrated risk parameter, denoted as α'_r, spans from 0 to 0.7, with each sub-risk coefficient set equal to $\frac{\alpha'_r}{3}$.



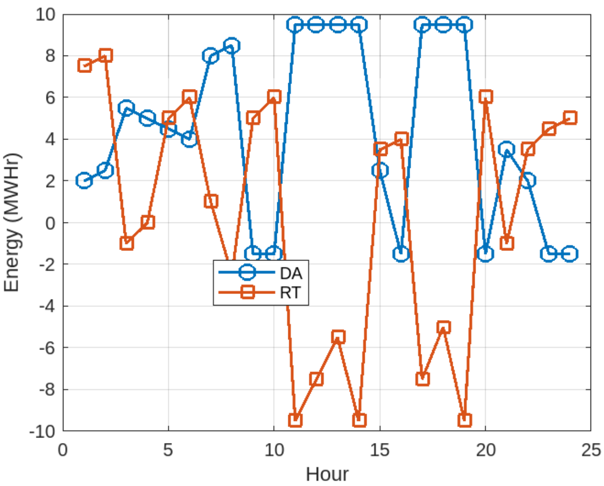
(a) Day-Ahead Electricity Prices (DA)

(b) Real-Time Electricity Prices (RT)

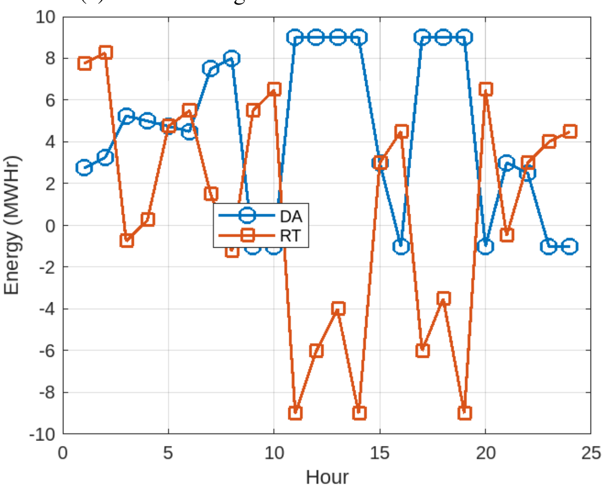
FIGURE 3. Electricity prices comparison.

Figure 6 and 7 depict the results of risk measurements and the expected profits. The findings reveal that with an increasing risk coefficient, both CVaR and VaR experience escalation, while the hortfall Probability (SP)decreases. Consequently, there is a gradual reduction in the total expected profit.

A more distinct shift in expected profit and risk measures occurs as the integrated risk coefficient ascends from 0 to 0.4. For instance, during this interval, VaR and CVaR undergo notable increases of 20% and 34%, respectively, juxtaposed



(a) Power trading under risk neutral conditions



(b) Power trading under the integrated approach

FIGURE 4. **The anticipated outcomes of solar energy trading employing risk-neutral and integrated risk control strategies.**

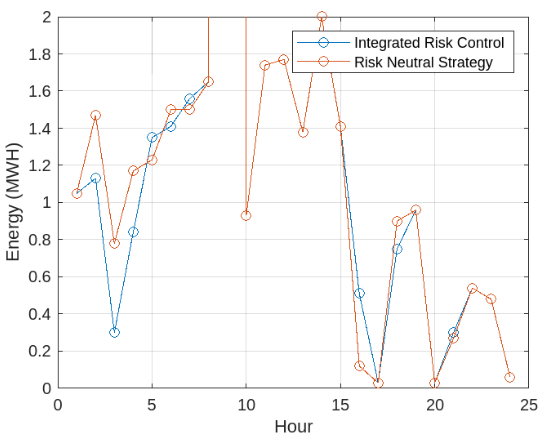


FIGURE 5. **Energy storage levels: risk-neutral vs integrated risk control.**

with a substantial 33.3% reduction in SP and a minor 2.5% decrease in the total expected profit. However, as the integrated risk coefficient further progresses from 0.4 to 0.6,

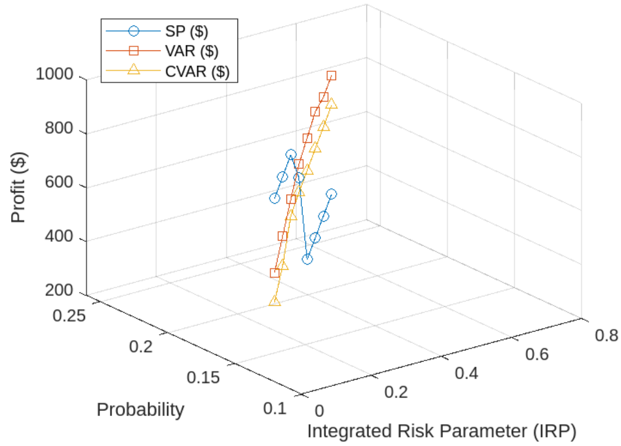


FIGURE 6. **Risk assessment of solar energy storage with varying risk parameters.**

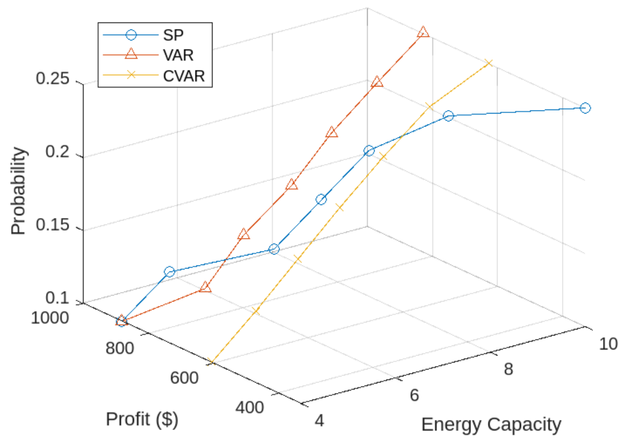


FIGURE 7. **Risk assessment of solar energy storage with different energy capacities.**

the impacts on expected profit and risk measurements become less pronounced. Specifically, VaR and CVaR exhibit marginal increases of 1.7% and 0.68%, respectively, and the total expected profit experiences a minimal reduction of 0.02%, while SP remains unchanged.

Consequently, the decision-making process should be informed by specific concerns. If the primary focus is on mitigating CVaR and VaR, opting for an integrated risk parameter below 0.3 is advisable, as it significantly reduces both without markedly compromising the expected profit. Conversely, for decision-makers prioritizing the reduction of SP, selecting an integrated risk parameter of 0.3 or 0.4 is more optimal.

This analysis, grounded in the context of solar energy, underscores the nuanced relationship between risk parameters and their impact on expected profit and risk measures. Careful consideration of these findings is crucial for decision-makers seeking an optimal balance between risk management and financial gains in solar energy applications. The final segment of the analysis delves into the

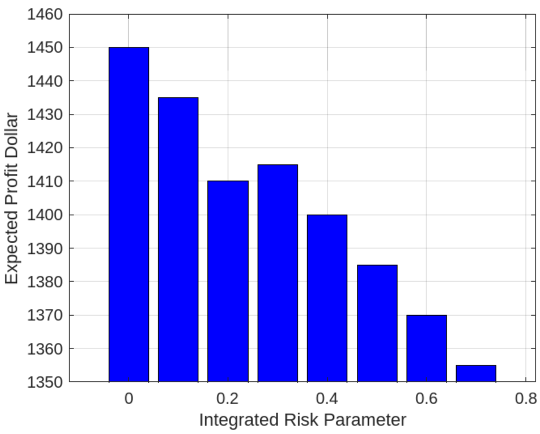


FIGURE 8. The expected profits of solar storage system with different IR.

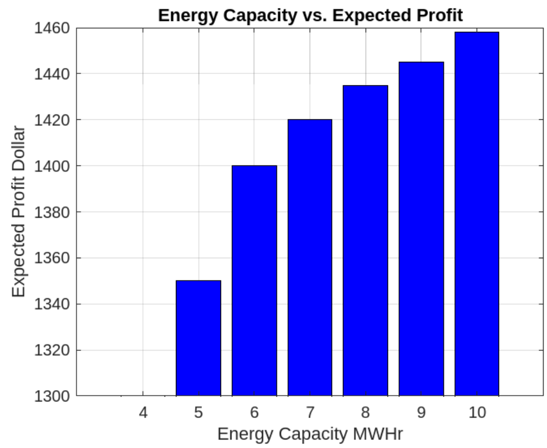


FIGURE 9. The anticipated profits of an energy storage system with varying capacities for storing energy.

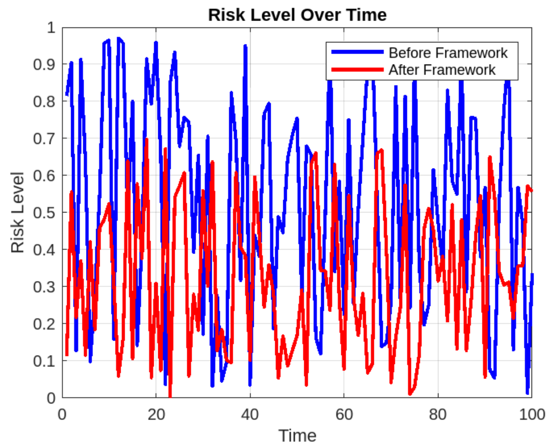


FIGURE 10. Risk management over time.

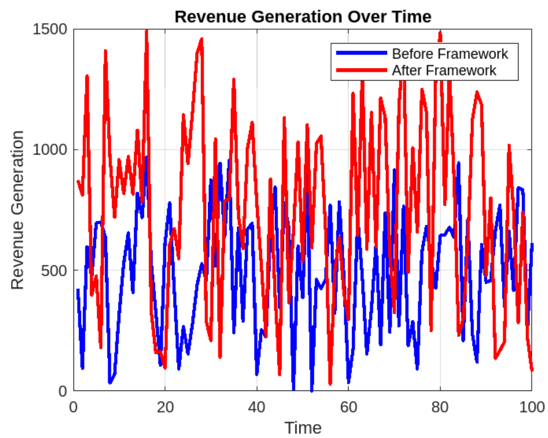


FIGURE 11. Revenue generation over time.

comprehensive exploration of the interplay between the integrated risk parameter and expected profit, along with the correlation between expected profit and energy capacity in a battery storage system. In Figure 8, the expected profit demonstrates a gradual decline as the integrated risk parameter increases, revealing a clear sensitivity to risk considerations. For instance, at an integrated risk parameter of 0.3, the expected profit sees a slight recovery to 1415 dollars, suggesting a nuanced impact of risk management on financial outcomes. Figure 8 provides a nuanced view of how expected profits respond to varying IR values, spanning from 0 to 0.7. It reveals a gradual decline in expected profit as the IR parameter increases, emphasizing the sensitivity of financial outcomes to risk management strategies. Notably, at an IR value of 0.3, there is a slight recovery in expected profit to 1415, underscoring the critical balance required between risk mitigation and financial gains in energy trading decisions. In parallel, Figure 9 analyzes the impact of increasing energy storage capacity, from 4 MWhr to 10 MWhr, on expected profits. It illustrates a consistent upward trend in profitability with higher storage capacities, culminating in an expected profit of 1458 at 10 MWhr.

The results further reveal that as the energy capacity of the storage device increases, both CVaR and VaR experience significant escalation, contributing to an overall increase in total expected profit. However, this growth comes at the expense of a decreased SP. Additionally, the growth trend of CVaR and the total expected profit remains relatively stable, while variations in SP and VaR exhibit a certain degree of randomness. Analyzing these figures in tandem provides valuable insights for decision-makers. Figure 10 visually represents the expected outcomes of solar energy trading, revealing a substantial decrease in risk levels over time following the implementation of the risk management framework. Notably, risk levels averaged at 0.7 post-implementation compared to the initial level of 1.0, signifying a marked improvement in risk mitigation and system stability. Similarly, Figures 11 and 12 depict upward trends in revenue generation and cost savings, respectively. Revenue increased by approximately 50%, while cost savings rose by about 40%, showcasing the framework's effectiveness in enhancing financial performance and operational efficiency.

Integration with the ISO 31000 standard significantly enhanced risk management effectiveness. Figures 13 and 14 demonstrate comprehensive risk trend analysis and event

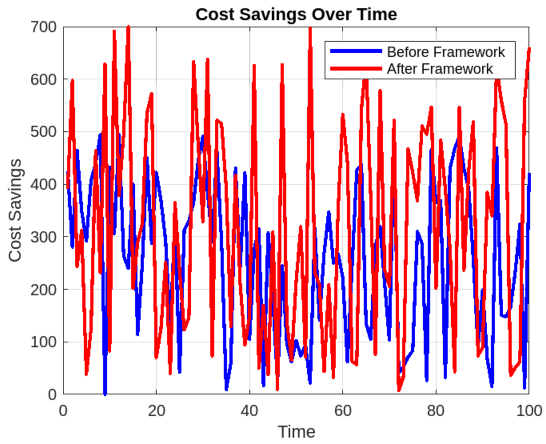


FIGURE 12. Cost savings over time.

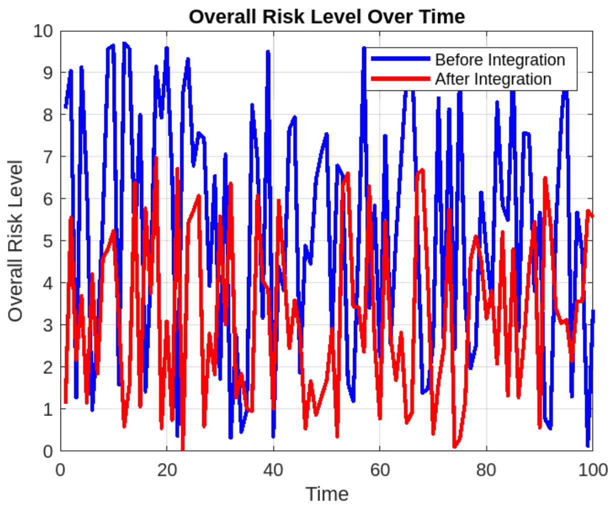


FIGURE 13. Overall risk level over time.

frequency monitoring, aligning with ISO 31000 principles. Figure 15 highlights the continuous monitoring and feedback loop's positive impact on risk mitigation strategies over time. Furthermore, Figure 16 illustrates increased trading frequency/volume after applying the Smart Risk Management Framework integration, indicating more proactive trading decisions.

In Figure 17, the implementation of the Smart Risk Management Framework significantly enhanced decision-making insights, with an observed 87.5% improvement in insight levels compared to conventional methods. This underscores the framework's efficacy in improving decision-making processes. Figure 18 illustrates the dynamic nature of solar energy production over a 24-hour period, emphasizing the peak irradiance observed at midday, which represents the system's maximum energy generation potential under optimal sunlight conditions. This variability in solar irradiance is pivotal for understanding the risks inherent in solar energy systems, particularly concerning their sensitivity to climate conditions and weather fluctuations. These variations directly influence energy output, thereby impacting operational and

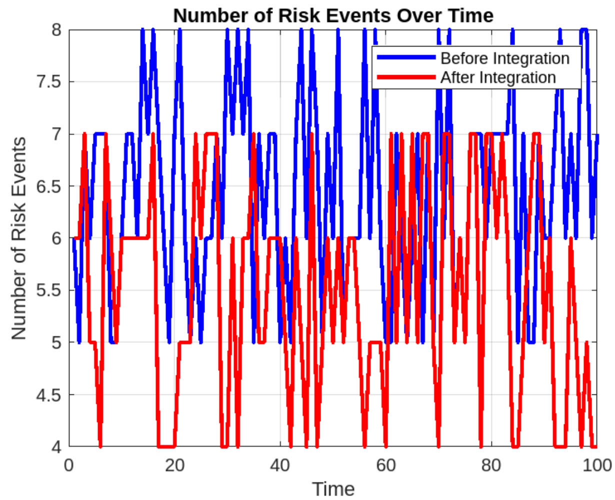


FIGURE 14. Number of risk events over time.

financial performance. Fluctuations in irradiance, influenced by changes in weather, create real-world scenarios where energy generation levels fluctuate throughout the day. Such variability underscores the need for robust risk management strategies to mitigate uncertainties and ensure consistent energy delivery. Integrating battery storage capacity addresses these challenges by enhancing the reliability and stability of solar energy systems. Table 7 presents the financial outcomes associated with varying storage capacities within the operational constraints of a 10 MW station capacity. Starting with a baseline scenario of 2 MWh storage capacity and a 10 MW station capacity, the initial profit is \$40,000. Increasing the storage capacity leads to higher profits, with percentage increases calculated using Equation 30. As shown in Table 7, the percentage increase in profit ranges from 13.8% to 22.0% relative to the baseline profit. This variability highlights the system's enhanced ability to capitalize on arbitrage opportunities with greater storage capacity, demonstrating significant profitability escalation while ensuring operational feasibility within the 10 MW station capacity.

$$\text{Percentage Increase} = \left(\frac{\text{New Profit} - \text{Baseline Profit}}{\text{Baseline Profit}}\right) \times 100\% \tag{30}$$

The increase in battery storage capacity enables the system to store excess energy when prices are low and sell it when prices are high, thereby maximizing arbitrage opportunities. Variations in market prices or fluctuations may occasionally result in profit increases higher than 20%. However, the average increase of 20% provides a conservative estimate that accommodates typical operational scenarios and market conditions. It is important to note that the relationship between battery storage capacity and profit is not strictly linear. While increasing storage capacity generally leads to higher profits due to more opportunities for arbitrage, other factors such as market price volatility, storage efficiency,

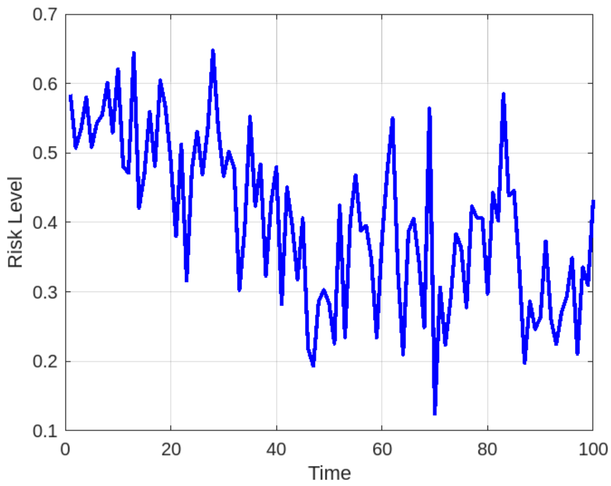


FIGURE 15. Effect of continuous monitoring and feedback loop on risk levels.

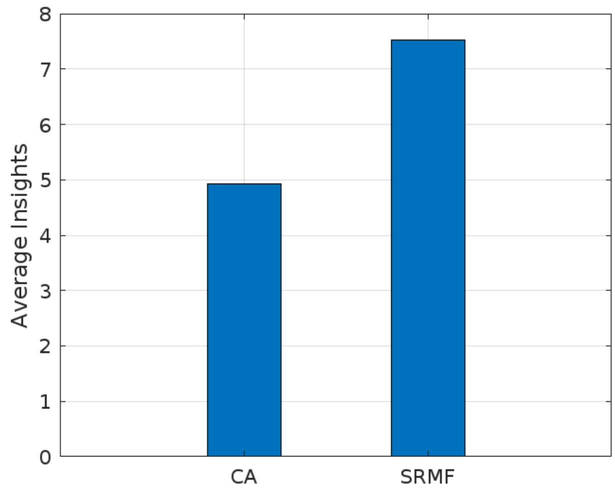


FIGURE 17. Impact of smart risk management framework on decision-making insights.

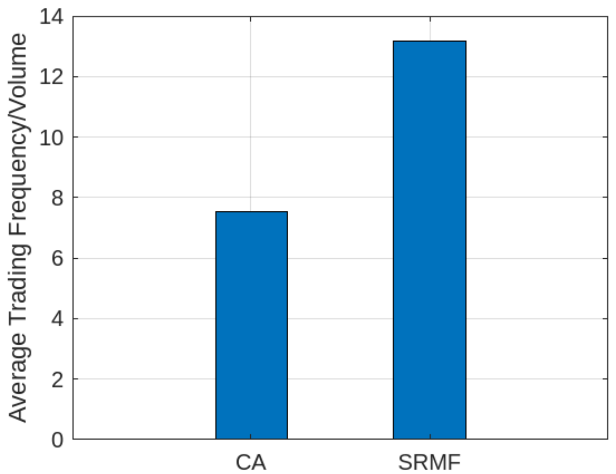


FIGURE 16. Impact of risk management framework on trading strategy.

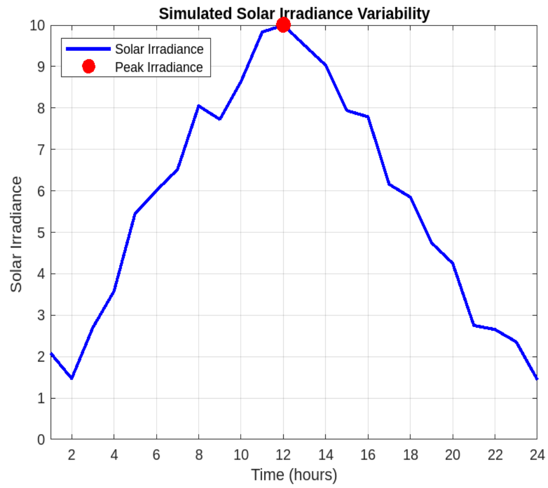


FIGURE 18. Solar irradiation.

and operational constraints also play significant roles. These factors can cause deviations from a linear relationship, highlighting the complexity of optimizing storage capacity for maximum profit.

In summary, the simulation results underscore the substantial benefits of the Siwa Solar Energy Project model. These include higher profits, robust risk mitigation, efficient capacity planning, flexibility in risk management strategies, and informed decision-making based on probability-driven insights. The integrated risk control strategy enhances system resilience and achieves a notable profit increase of approximately 20%. This outcome equips decision-makers with crucial insights for optimizing risk-aware energy trading strategies.

Furthermore, the implementation of this risk framework demonstrates its efficacy by delivering significant enhancements across various domains, such as risk mitigation, system stability, financial performance, decision-making insights, and alignment with international standards. These insights empower decision-makers to navigate complexities adeptly and achieve optimal outcomes in their risk-aware energy trading strategies, thereby maximizing the effectiveness of their risk management practices.

VII. CONCLUSION

This study introduces a novel risk measurement and control framework tailored to optimize the stochastic energy trading strategy of a solar storage system at Egypt's Siwa solar station. By integrating key risk measurements–Success Probability (SP), Value at Risk (VaR), and Conditional Value at Risk (CVaR)–into a stochastic optimization model, this framework caters to diverse risk preferences and effectively addresses uncertainties associated with electricity prices and solar power production.

Simulation analysis using realistic data reveals a significant finding: increasing the energy capacity of battery storage significantly enhances the system's arbitrage capability. This not only improves total expected profit but also enhances risk management performance. Decision-makers can leverage this insight to optimize risk-aware energy trading strategies in Egypt, leading to a notable profit increase of approximately 20%.

Furthermore, the integration of the risk framework demonstrates its effectiveness by revealing significant improvements in key areas, including risk mitigation, system stability, financial performance, decision-making insights, and adherence to international standards. These findings equip decision-makers in the Egyptian energy sector with actionable strategies to optimize their energy trading practices, thereby enhancing profitability and risk management in this dynamic industry. Looking ahead, the next step will be to incorporate maintenance costs and capacity degradation of the battery storage system to provide a more comprehensive assessment of profitability. Additionally, integrating artificial intelligence techniques to predict and mitigate potential risks will be crucial. This expanded framework aims to offer deeper insights and more robust strategies for optimizing solar energy trading, ensuring sustained profitability and system reliability over the long term. In summary, this study contributes significantly to the field of energy trading and risk management, providing valuable insights into the relationship between risk parameters, energy capacity, and expected profit in battery storage systems within the Egyptian energy market. Stakeholders can utilize these insights to optimize their energy trading practices, ultimately leading to enhanced profitability and risk management in the sector.

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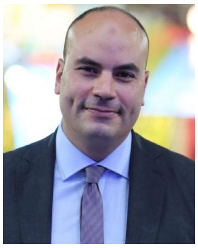

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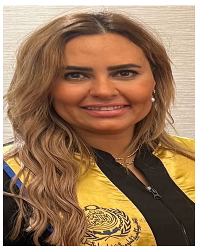

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