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# A Risk Preference-Based Optimization Model for User-Side Energy Storage System Configuration from the Investor's Perspective

**Jinming Gao [1], Yixin Sun [1] and Xianlong Su [1,2,*]**

[1] Department of Computer Science and Engineering, Paichai University, 155-40 Baejae-ro, Daejeon 35345, Republic of Korea; 2314711@pcu.ac.kr (J.G.); 2314709@pcu.ac.kr (Y.S.)

[2] School of Electrical and Electronic Engineering, Chongqing University of Technology, Chongqing 400054, China

* Correspondence: sxl_2012@cqut.edu.cn

**Abstract:** To enhance the utilization of emerging energy sources, the application of battery energy storage systems (BESSs) was increasingly explored by investors. However, the immature development of BESS technologies introduced supply–demand imbalances, complicating the establishment of standardized cost analysis frameworks for potential investments. To address this challenge, a hybrid optimization model for a user-side BESS was developed to maximize total net returns over the system's entire life cycle. The model accounted for factors such as energy storage arbitrage revenue, government tariff subsidies, reductions in electricity transmission fees, delays in grid upgrades, and overall life cycle costs. Conditional value-at-risk (CVaR) was employed as a risk assessment metric to provide investment allocation recommendations across various risk scenarios. An example analysis was conducted to allocate and evaluate the net returns of different battery types. The results demonstrated that the model identified optimal investment strategies aligned with investors' risk preferences, enabling informed decision-making that balanced returns with operational stability. This approach enhanced the resilience and economic viability of user-side energy storage configurations.

**Keywords:** user-side energy storage; conditional risk value; life cycle; investment analysis



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## 1. Introduction

The rise in clean energy initiatives has underscored the significance of battery energy storage systems (BESSs) as a pivotal component, serving as a buffer against power generation fluctuations and load irregularities [1]. The technology's applications span multiple sectors, encompassing user-side, distribution-side, and new energy generation storage [2–4]. Specifically, user-side energy storage systems interact directly with end-user demands, distinguishing them from power-side storage solutions. These systems are pivotal for harmonizing clean energy production, managing user load profiles, optimizing time-of-use tariffs, and potentially decreasing overall electricity consumption [5]. The economic benefits derived from these functionalities have not gone unnoticed, leading to significant external investment from stakeholders such as corporate entities and energy service companies [6]. This strategic importance and multifaceted utility underscore the growing relevance of BESSs in advancing sustainable energy practices.

With the introduction of various incentives and compensation policies aimed at promoting the development of user-side distributed electric energy storage facilities, research on user-side energy storage configurations has received increasing attention [7]. Unlike grid-side energy storage, user-side energy storage operates under a distinct operational paradigm, necessitating a heightened focus on its economic viability to attract investor interest [8]. Xia Y et al. [9] consider the stochastic nature of distributed generation and establish an optimal cost model, which is solved by accelerated particle swarm optimization and a Jaya optimization technique-based interior point algorithm, to obtain the storage capacity. Singh B et al. [10] establish an integrated energy storage model considering demand response, electric vehicle load, and clean energy consumption and analyze the economic benefits and feasibility of different combinations. By analyzing the economic benefits and feasibility of various storage configurations, their model offers insights into how different combinations can improve cost-effectiveness and reliability.

Previous research aligns closely with various optimization strategies for configuring and optimally scheduling user-side energy storage systems [11], demonstrating significant potential. However, practical applications of energy storage often face operational risks [12]. As user-side energy storage systems become increasingly complex, they must contend with uncertainties introduced by distributed energy resources and fluctuating load demands [13]. Currently, stochastic optimization and robust optimization are widely used to tackle these uncertainties [14]. For instance, Ibrahim M. et al. [15] apply Monte Carlo simulations to generate scenarios that model uncertainties in renewable generation, electric vehicle charging, and microgrid demand, solving the resulting optimization problem with a transient search algorithm to develop an optimal dispatch scheme. Similarly, Zhang M. et al. [16] propose a robust optimization approach using a budget uncertainty set to enhance the resilience and economic efficiency of energy storage systems amid wind power fluctuations and other real-world uncertainties.

Despite significant advances in methods for analyzing uncertainty within energy storage optimization, relatively few studies have addressed the critical aspects of risk assessment and management. Energy storage investors often lack concrete, quantifiable guidance on managing investment risks, which leaves them with limited insight into potential returns and exposure to extreme outcomes. This gap is particularly pronounced in scenarios characterized by high volatility, such as fluctuating energy prices, renewable energy generation variability, and unpredictable load demands. To address this challenge, this paper introduces the Conditional Value-at-Risk (CVaR) methodology [17], a robust tool for modeling and quantifying uncertainty risks associated with energy storage system operations.

CVaR goes beyond traditional risk measures by focusing on tail risk, i.e., the potential for extreme losses. By providing a more comprehensive risk profile, CVaR equips investors with actionable insights for strategic decision-making under uncertainty. This approach empowers energy storage investors to design risk-adjusted strategies that balance potential returns with resilience to adverse events. For instance, CVaR has proven effective in financial portfolio management and renewable energy planning; applying it in energy storage optimization provides a systematic framework to account for extreme risks. By utilizing CVaR, this study offers practical solutions to optimize user-side energy storage investments, enabling investors to maximize returns while minimizing losses. While existing studies focus primarily on single battery chemistries for energy storage, limited research has explored the integration of multiple battery media in user-side configurations. This paper addresses this limitation by conducting a comprehensive analysis of the operational characteristics of various battery types and their potential synergies. Specifically, four configurable battery options are examined: sodium–sulfur (NAS) batteries, vanadium redox (VRB) batteries, valve-regulated lead–acid (VRLA) batteries, and lithium-ion (Li-ion) batteries [18]. Each of these battery types possesses unique attributes in terms of cost, performance, lifespan, and risk, making their combined use a promising avenue for enhancing flexibility and resilience.

To optimize the deployment of these heterogeneous energy storage systems, this paper proposes a hybrid optimization model tailored to accommodate the distinct characteristics of each battery type. The model incorporates CVaR to address risk preferences, providing customized configuration recommendations for investors. By leveraging the computational capabilities of GAMS, the model efficiently solves the mixed-integer programming problem, ensuring robust and accurate solutions. This hybrid optimization framework not only improves the operational performance of user-side energy storage but also empowers investors with flexible strategies that align with their risk tolerance and economic goals.

## 2. System Description and Modeling

On the user side, energy-based energy storage systems are commonly used, primarily for peak shaving to match power supply with load demand effectively. These systems maximize economic benefits by capitalizing on time-of-use pricing strategies, such as charging during low-tariff periods and discharging during high-tariff periods, thus achieving cost savings and revenue generation for users [19]. The deployment location of user-side energy storage is crucial for optimizing system performance, enhancing load balancing, and supporting reliable power supply. The installation location of user-side energy storage is shown in Figure 1.

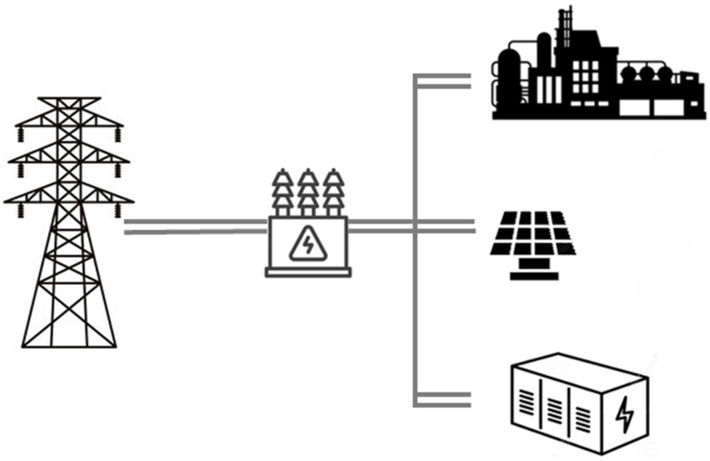

**Figure 1.** Schematic diagram of installation position of energy storage on the user's side.

The BESSs that have been widely used commercially and are in demonstration projects include NAS, VRB, VRLA, and Li-ion. This article considers that when factors such as the use environment are satisfied, these four types of batteries are configured at the same time, and the operational risks and economic benefits are comprehensively considered to configure them reasonably. For the convenience of analysis, the spatial factors of different batteries are simplified and reflected in the cost.

### 2.1. BESS Economic Benefit Model

This article takes the maximum revenue within the battery's full life cycle as the objective function, and its expression is

$$\begin{aligned} \max \quad C_{\text{total}} &= S_{\text{offer}} + S_{\text{gov}} + S_{\text{energy}} + S_{\text{grid}} \\ &\quad - C_{\text{CVaR}} - C_{\text{const}} - C_{\text{o\&m}} - C_{\text{market}} \end{aligned} \tag{1}$$

In the formula, $C_{\text{total}}$ is the total revenue of the system, and $S_{\text{offer}}$, $S_{\text{gov}}$, $S_{\text{energy}}$, $S_{\text{grid}}$ are respectively the arbitrage of "Low tariffs for charging, high tariffs for discharging" during the entire life cycle of the battery, the subsidy income issued by the government to encourage the installation of user-side batteries, and the energy transfer costs reduced by the battery and the avoidance of power grid upgrades. $C_{\text{CVaR}}$, $C_{\text{const}}$, $C_{\text{o\&m}}$, $C_{\text{market}}$ are system condition risk value, system construction cost, system maintenance cost, and electricity purchase and sale cost, respectively.

In addition, user-side energy storage can be configured with photovoltaics. In order to describe the risks faced when optimizing the configuration of user-side energy storage, the uncertainty of simulated variables needs to be simulated in the model. This paper uses a mathematical method of multiple scenario sets to simulate the uncertainty problem in the model. Define s as the photovoltaic unit output scenario, the number of which is $N_{\text{S}}$, and the probability of each scenario occurring is $\pi_{\text{S}}$. The maximum daily photovoltaic output can be obtained from the day's light intensity and is calculated as follows:

$$P_{t,s}^{\text{pv}} = \eta_{\text{ct}} \cdot S_{\text{CA}} \cdot G_{t,s} \tag{2}$$

In the formula, $\eta_{\text{ct}}$ is the photovoltaic array conversion efficiency, $S_{\text{CA}}$ is the photovoltaic array area, and $G_{t,s}$ represents the solar radiation intensity during $t$ period.

Peak and valley electricity prices are mostly used on the user side. In view of this, the energy storage system can charge at low load times and discharge at peak load times, thereby achieving arbitrage. The income is

$$Q_1^{\text{s}} = \sum_{i=1}^{I} \sum_{t=1}^{24} \left( P_{t,s,i}^{\text{dis}} U_{t,s,i}^{\text{dis}} - P_{t,s,i}^{\text{ch}} U_{t,s,i}^{\text{ch}} \right) \lambda_{t,s}^{\text{e}} \tag{3}$$

$$S_{\text{offer}} = \sum_{s=1}^{N_s} \pi_s \sum_{a=1}^{A} Q_1 D \left( \frac{1+i_{\text{r}}}{1+d_{\text{r}}} \right)^a \tag{4}$$

Among them, $Q_1^{\text{s}}$ is the current one-day arbitrage income of energy storage; $\pi_s$ is the scenario occurrence probability corresponding to the $s$ photovoltaic scenario; $N_s$ is the total possible photovoltaic scenarios; $P_{t,s,i}^{\text{dis}}$, $P_{t,s,i}^{\text{ch}}$ are, respectively, the discharge of the $i$ battery in the $s$ electricity price scenario at time $t$ power and charging power; $U_{t,s,i}^{\text{dis}}$, $U_{t,s,i}^{\text{ch}}$ are, respectively, whether the $i$ battery is discharged/charged under the $s$ electricity price scenario at time $t$ and are 0–1 variables; $\lambda_t^{\text{e}}$ is the electricity prices in the energy market; $D$ is the number of days of battery utilization in a year; $i_{\text{r}}$ is currency expansion rate; $d_{\text{r}}$ is the discount rate; the subscripts $i$, $t$, $s$, and a, respectively, represent the $i$ battery, time $t$, photovoltaic scenario in $s$, and year $a$;

In addition, the constraints satisfied by the state variables of charging and discharging are

$$U_{t,s,i}^{\text{dis}} + U_{t,s,i}^{\text{ch}} \leq 1 \tag{5}$$

$$U_{t,s,i}^{\text{dis}} \cdot U_{t,s,i}^{\text{ch}} = 0 \tag{6}$$

Referring to the support policies for the energy storage industry, there are currently two basic forms of government subsidies: (1) initial construction investment subsidies for energy storage and (2) electricity price subsidies. The two subsidy forms focus on subsidies for investment and construction and operating costs, respectively. This article adopts electricity price subsidies. The subsidy income issued by the government to encourage the installation of user-side batteries is

$$Q_2^{\text{s}} = \sum_{i=1}^{I} \sum_{t=1}^{24} \left( P_{t,s,i}^{\text{dis}} \cdot \lambda^{\text{gov}} \right) \tag{7}$$

$$S_{\text{gov}} = \sum_{s=1}^{N_s} \pi_s \sum_{a=1}^{A} Q_2 D \left( \frac{1+i_{\text{r}}}{1+d_{\text{r}}} \right)^a \tag{8}$$

Among them, $Q_2^{\text{s}}$ is the current government subsidy income received for one day of energy storage; $\lambda^{\text{gov}}$ is the government's additional subsidy electricity price for energy storage discharge capacity.

In the power market, power suppliers and consumers need to pay certain power operating costs to the distribution network. User-side energy storage is directly installed on the power side, which facilitates direct power transmission and saves a lot of power transmission costs. Therefore, the profit calculation of the BESS from reducing transfer fees is as follows:

$$Q_3^{\text{s}} = \sum_{i=1}^{I} \sum_{t=1}^{24} \left( P_{t,s,i}^{\text{dis}} - P_{t,s,i}^{\text{ch}} \right) \lambda_t^{\text{r}} \tag{9}$$

$$S_{\text{energy}} = \sum_{s=1}^{N_s} \pi_s \sum_{a=1}^{A} Q_3 M \left( \frac{1+i_{\text{r}}}{1+d_{\text{r}}} \right)^a \tag{10}$$

In the formula, $Q_3$ is the electric energy operating cost reduced by using the current battery for one month; $\lambda_t^r$ is the electric energy transmission cost of the distribution network during period $i$ in the month; and $M$ = 12 is the number of months included in a year.

The power consumption of industrial and commercial users fluctuates to a certain extent. The industrial power demand may increase in a certain period of time and even exceed the rated capacity of its preset transformer. It is often necessary to transform it by adding transformers or replacing transmission lines, which takes a long time and is costly. However, after the installation of user-side energy storage components, dynamic capacity expansion is achieved, flexibility is higher, and transformer upgrades can be delayed, increasing the service life of the equipment and greatly reducing the cost. The investment cost is calculated as follows:

$$\Delta n = \frac{\lg(1+\mu)}{\lg(1+\tau)} \tag{11}$$

$$S_{\text{grid}} = Q_4 = C_{\text{inv}} [1 - \frac{(1+i_{\text{r}})^{\Delta n}}{(1+d_{\text{r}})^{\Delta n}}] \tag{12}$$

In the formula, $\mu$, $\tau$ are the annual growth rate of the load and the peak shaving rate of energy storage, respectively; $\Delta n$ represents the number of years to delay the power grid upgrade; $Q_4$ represents the benefits of delaying the power grid upgrade; and $C_{\text{inv}}$ is the construction cost of the power grid upgrade.

The cost of the battery is divided into initial investment cost and later operation and maintenance cost, which depends on the rated capacity and rated charging and discharging power of the BESS installation. The specific expression is

$$C_{\text{const}} = \sum_{i}^{I} C_i^{\text{p}} \overline{P}_i + C_i^{\text{e}} \overline{S}_i \tag{13}$$

In the formula, $C_i^{\text{p}}$ is the unit charge/discharge cost of different types of BESSs, $\overline{P}$ is the rated charge/discharge power of the battery, $C_i^{\text{e}}$ is the unit capacity cost of different types of BESSs, and $\overline{S}_i$ is the rated capacity of the battery.

The operation and maintenance cost of the BESS mainly depends on the rated power of the battery, and its calculation formula is as follows:

$$Q_{\text{o\&m}} = \sum_{i}^{I} C_i^{\text{m}} \overline{P}_i \tag{14}$$

$$C_{\text{o\&m}} = \sum_{a=1}^{A} Q_{\text{o\&m}} \left( \frac{1+i_{\text{r}}}{1+d_{\text{r}}} \right)^{a} \tag{15}$$

In the formula, $C_i^{\text{m}}$ is the operation and maintenance cost per unit charge/discharge power of the battery, and $Q_{\text{o\&m}}$ is the annual operation and maintenance cost of the battery.

Coordination between BESSs and photovoltaic systems can partially reduce the risk of power supply imbalance. However, complete avoidance of such imbalances is not possible. To ensure a reliable power supply, it is mandated to purchase power from the superior power grid in case of insufficient supply. The market transaction cost can be calculated as follows:

$$C_{\text{market}} = \sum_{t=1}^{24} \sum_{s=1}^{N_s} \pi_s \left( U_{t,s}^{\text{buy}} P_{t,s}^{\text{buy}} - U_{t,s}^{\text{sold}} P_{t,s}^{\text{sold}} \right) \tag{16}$$

In the formula, $P_{t,s}^{\text{buy}}$, $P_{t,s}^{\text{sold}}$, respectively, represent the power purchased/sold by the superior power grid. $U_{t,s}^{\text{buy}}$, $U_{t,s}^{\text{sold}}$ are 0–1 variables, indicating whether to buy/sell electricity to the market at time $t$.

The system cannot purchase or sell electricity to the market at the same time. The market transaction power constraints are as follows:

$$P_{t,s}^{\text{buy}} \leq P_t^{\text{maxbuy}} \tag{17}$$

$$P_{t,s}^{\text{sold}} \leq P_t^{\text{maxsold}} \tag{18}$$

$$U_{t,s}^{\text{buy}} + U_{t,s}^{\text{sold}} \leq 1 \tag{19}$$

In the formula, $P_t^{\text{maxbuy}}$, $P_t^{\text{maxsold}}$ are, respectively, the maximum market power purchase/sales.

### 2.2. Conditional Risk Value Theory and Its Applications

The primary goal of an investment portfolio is to maximize returns while minimizing risk. For user-side energy storage, the rising share of renewable energy sources introduces significant uncertainties due to the variability and intermittency of renewable output, often causing power supply disruptions that increase revenue risks [20]. Additionally, the operational risks of batteries on the user side vary widely depending on the maturity and reliability of the battery technology. To manage these risks effectively, it is essential to strategically integrate different types of batteries, allocate appropriate capacities and charge/discharge rates, and conduct thorough risk assessments for these configurations. Given these layered risks, a robust framework is necessary to quantify and manage potential financial impacts, helping investors mitigate losses while optimizing returns.

Risk simulations typically rely on stochastic or historical approaches. In this study, the historical simulation method is applied to assess potential loss risks during the optimal configuration of user-side energy storage systems. To enhance the analysis, the CVaR model is used to quantify risk more effectively [21]. Unlike the traditional VaR method, which fails to capture extreme losses beyond a given threshold, CVaR is particularly valuable for energy storage optimization as it considers “tail risk”, reflecting the more severe potential losses that could occur beyond a set confidence level. This makes CVaR well-suited for user-side storage applications, where renewable energy intermittency and battery performance variability necessitate precise risk management. The CVaR calculation formula is as follows:

$$CVaR_{\beta} = \frac{1}{1-\beta} \int_{f(x,y) \geq VaR_{\beta}(x)} f(x,y) \rho(y) dy \tag{20}$$

The above analytical expression $VaR_\beta(x)$ is difficult to solve, and the value of CVaR is usually replaced by a transformation function $F_\beta(x,\alpha)$:

$$F_\beta(x,\alpha) = \alpha + \frac{1}{1-\beta}\int\limits_{y\in R^m}[f(x,y)-\alpha]^+\rho(y)dy \tag{21}$$

In the formula, $[f(x,y)-\alpha]^+$ represents $\max\{f(x,y)-\alpha,0\}$; $\alpha$ is the value of VaR.

The transformation function $F_\beta(x,\alpha)$ is usually calculated using the following estimation formula:

$$\widetilde{F}_\beta(x,\alpha) = \alpha + \frac{1}{q(1-\beta)}\sum_{k=1}^{q}[f(x,y_k)-\alpha]^+ \tag{22}$$

In the formula, $y_1,\ldots,y_{\mathrm{q}}$ is the $y$ samples of $q$ but $CVaR_\beta = \min\widetilde{F}_\beta(x,\alpha)$.

Therefore, the CVaR theory is used to measure the risk of the BESS, and the risk coefficient is used to express the investors' preference for risk:

$$\delta = \alpha + \frac{1}{1-\beta}\sum_{s=1}^{N_s}\pi_s \cdot z_s^k \tag{23}$$

$$C_{\mathrm{CVaR}} = L\delta \tag{24}$$

In the formula, $L$ is the risk preference coefficient; $\alpha$ is the value of VaR; $\delta$ is the value of CVaR; $\beta$ is the confidence level set by investors.

A dummy variable $z_k^{\mathrm{wsp}} = [f(x,y)-\alpha]^+$ is introduced to represent the loss in the conditional value at risk that exceeds VaR. Define the loss function, whose value is equal to the negative value of the total return. Use relaxation techniques to transform this constraint into the following two inequalities:

$$z_s^k \geq 0 \tag{25}$$

$$z_s^k \geq -\begin{pmatrix} Q_1^{\mathrm{s}} + Q_2^{\mathrm{s}} + Q_3^{\mathrm{s}} + S_{\mathrm{grid}} - C_{\mathrm{const}} - C_{\mathrm{o\&m}} \\ -\sum\limits_{t=1}^{24}\left(U_{t,s}^{\mathrm{buy}}P_{t,s}^{\mathrm{buy}} - U_{t,s}^{\mathrm{sold}}P_{t,s}^{\mathrm{sold}}\right) \end{pmatrix} - \alpha \tag{26}$$

*2.3. BESS Full Life Cycle Charge and Discharge Model*

During the entire life cycle, the BESS needs to satisfy energy conservation to enable battery recycling. The BESS energy conservation constraint is as follows:

$$\sum_{i=1}^{24}\left(P_{t,s,i}^{\mathrm{dis}} - P_{t,s,i}^{\mathrm{ch}}\eta_i\right) = 0 \tag{27}$$

In the formula, $\eta$ is the energy conversion efficiency of the battery. The conversion efficiency of batteries with different media is different.

During the charging process, the charging and discharging power constraints and the total discharge capacity constraints need to be satisfied, and the expression is as follows:

$$\overline{P}_i - P_{t,s,i}^{\mathrm{dis}} \geq 0 \tag{28}$$

$$\overline{P}_i - P_{t,s,i}^{\mathrm{ch}} \geq 0 \tag{29}$$

$$\sum_{t=1}^{24}P_{t,s,i}^{\mathrm{dis}} \leq \overline{E}_i \tag{30}$$

Energy storage and photovoltaics jointly participate in user power supply. During operation, the energy balance constraint is

$$P_{t,s}^{\mathrm{pv}} + \sum_{i=1}^{I}\sum_{t=1}^{24} P_{t,w,i}^{\mathrm{dic}} + P_{t,s}^{\mathrm{buy}} = \sum_{i=1}^{I}\sum_{t=1}^{24} P_{t,w,i}^{\mathrm{ch}} + P_{t}^{\mathrm{load}} + P_{t,s}^{\mathrm{sold}} \tag{31}$$

This article takes the total revenue within the entire life cycle of the BESS as the optimization goal and considers the risk value during the operation of the BESS. The general mathematical expression is as follows:

$$\begin{cases} \max f(x,y) \\ s.t\ h(x) = 0 \\ g(x) \le g(\overline{y}) \end{cases} \tag{32}$$

$h(x) = 0$ represents the equilibrium state where the power balance and battery charging and discharging constraints mentioned in this article are satisfied. $g(x)$ represents the cost and risk factors of BESS operation, and $g(\overline{y})$ represents the reference or benchmark values for these costs and risks, defining the acceptable thresholds or targets.

Among them, $x = \left(P_{t,s,i}^{dis}, P_{t,s,i}^{ch}\right)$ is the decision variable of the system and is a continuous variable. $y = \left(\overline{P}_i, \overline{E}_i\right)$, and it should be noted that since the power of a single converter is limited, the rated power $\overline{P}_i$ and rated capacity $\overline{E}_i$ of the energy storage system are discrete variables, so the proposed model is a typical hybrid optimization model.

### *2.4. GAMS Performs Model Solving*

Due to the complexity of the hybrid optimization model, which involves multiple variables and constraints, the solving process is quite challenging. Traditional methods struggle to efficiently handle such intricate optimization problems. To improve solution efficiency and ensure accuracy, we chose to use the commercial optimization software GAMS (42.1.0) for solving the model. GAMS possesses powerful mathematical modeling and optimization capabilities, making it well suited for handling large-scale nonlinear, multi-objective, and multi-constraint optimization problems [22,23], thereby providing reliable support for solving the model in this study.

The optimization problem in this study was addressed using GAMS, with the CPLEX solver applied to resolve the proposed mixed optimization problem. CPLEX exhibited strong performance in handling discrete variables (system power and capacity decisions) and continuous variables (charging/discharging rates) by utilizing advanced branch-and-bound algorithms. Its scalability facilitated the efficient management of large-scale problems involving thousands of variables and constraints, ensuring accurate results for complex energy storage configurations. The seamless integration of CPLEX with GAMS streamlined the workflow from model formulation to solution [24], enabling reliable and precise insights into optimal energy storage strategies, encompassing cost-effectiveness and risk analysis.

The optimization problem was addressed in GAMS through several critical steps. Initially, a detailed model was developed using the GAMS modeling language based on specific operational constraints, cost structures, revenue streams, and risk strategies for energy storage deployment on the user side. This step formalized the problem into a mixed optimization model, incorporating key decision variables and objective functions for energy storage configurations. Next, the model was solved using the CPLEX solver. CPLEX employed advanced branch-and-bound algorithms to efficiently navigate complex solution spaces, optimizing decision variables such as battery type selection and charging/discharging schedules while ensuring strict compliance with constraints and optimization goals. Finally, a comprehensive analysis of the results yielded detailed insights into the optimal energy storage configuration. These results included evaluations of investment costs, risk preferences, and system performance metrics, offering customized energy storage plans tailored to investors with diverse risk profiles. This research provides stakeholders with data-driven, actionable decision support, enabling them to achieve maximum returns aligned with strategic investment objectives while effectively mitigating potential risks.

## 3. Example Testing and Result Analysis

### *3.1. Parameter Description*

Figure 2 illustrates the annual solar irradiance data from 2018 to 2021 for users with optical storage at a specific location. Figure 3 presents the average annual market electricity price over the same period, calculated as the average of the four-year prices. Figure 4 depicts the annual average load data. The system considered in this study includes a PV system as the primary renewable energy source in conjunction with a BESS. The charging period for the BESS is from 23:00 to 9:00 the next day, aligning with lower electricity prices during off-peak hours and the absence of PV generation at night. The discharging period, from 9:00 to 23:00, is designed to coincide with daytime hours when PV generation is active, allowing the BESS to store excess PV power and discharge it during periods of high electricity demand or reduced PV output. This schedule reflects a load-shifting strategy aimed at optimizing PV utilization, minimizing grid reliance, and achieving economic benefits through electricity price arbitrage.

The BESS operates 250 days/year, utilizing four batteries (NAS, VRB, VRLA, Li-ion) with diverse performance parameters as configurable resources. See Table 1 for relevant parameters.

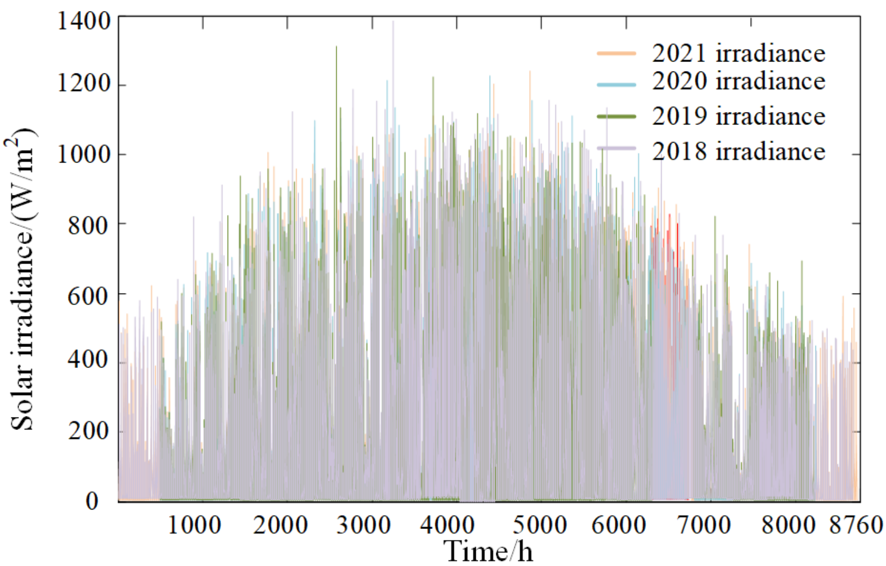


**Figure 2.** Lighting intensity data from 2018 to 2021.

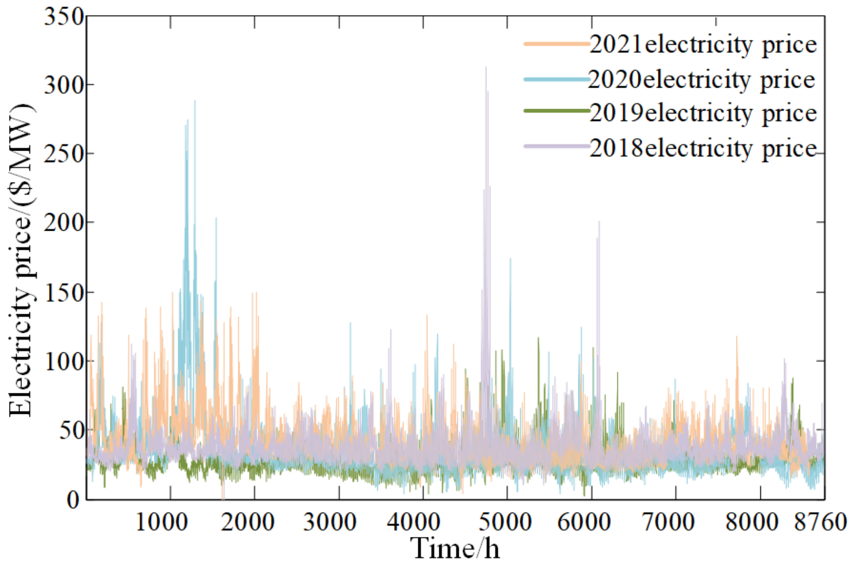


**Figure 3.** Real-time electricity price data from 2018 to 2021.

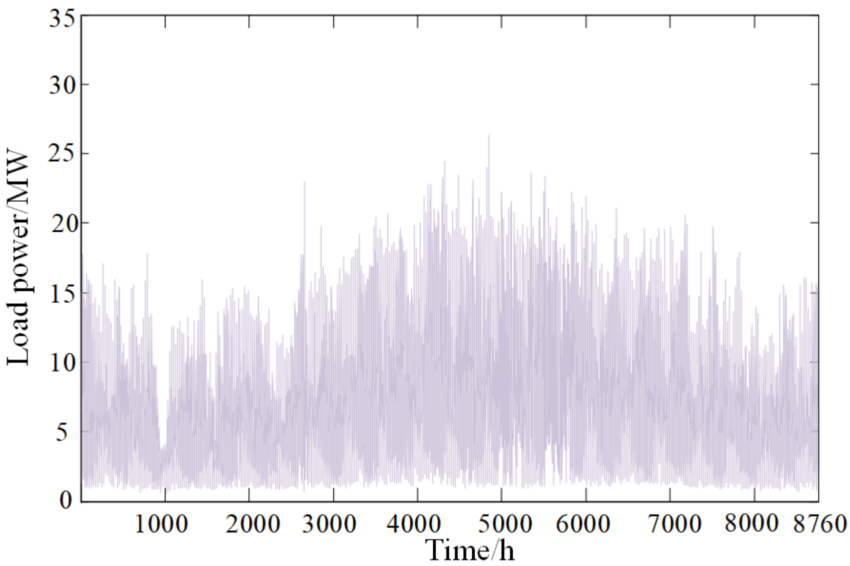


**Figure 4.** User load data diagram.

**Table 1.** Parameter information of different types of batteries.

| Parameter | NAS | VRB | VRLA | Li-Ion |
|---|---|---|---|---|
| Cp (USD/kW) | 300 | 320 | 230 | 288 |
| Ce (USD/kW·h) | 145 | 80 | 110 | 160 |
| Cm (USD/kW·a) | 9 | 9 | 11 | 10 |
| $\eta$/% | 80 | 70 | 85 | 90 |
| T/a | 15 | 15 | 10 | 15 |

The converter power and battery string rated capacity of the four types of batteries are 200 kW and 200 kW·h. The rated capacity of the BESS is 20–60 MW·h, and the rated charge/discharge power is 1–10 MW.

The conventional parameters used in this article are shown in Table 2:

**Table 2.** System parameters.

| Parameter | Numerical Value |
| --- | --- |
| PV conversion efficiency | 20% |
| Government subsidy income | 2.75 USD/MW·h |
| Electricity transmission cost | 20 USD/MW·h |
| Average annual load growth rate | 1.5% |
| Power grid upgrade and transformation cost | USD 300,000 |
| Inflation rate | 1.5% |
| Discount rate | 9% |

According to investors' preference for risk, user-side energy storage configuration plans are divided into four types according to the size of the risk coefficient: radical, more radical, more conservative, and conservative. The corresponding risk coefficients are shown in Table 3.

**Table 3.** Different investment types and risk information.

| Investors | Type | Risk Coefficient | Risk |
| --- | --- | --- | --- |
| A | Radical | 0.05–0.1 | High |
| B | More radical | 0.1–0.5 | Higher |
| C | More conservative | 0.5–1 | Lower |
| D | Conservative | 1–2 | Low |

### *3.2. Analysis of Calculation Example Results*

#### 3.2.1. Analysis of Economic Characteristics of Different Batteries

In order to analyze the economic characteristics and operational risks of each type of battery, an optimization analysis is first performed on the scenario of separately configuring a type of battery. The economic characteristics of the four types of batteries are shown in Table 4, The capacity configuration plan corresponding to this benefit analysis is shown in Table 5.

**Table 4.** Optimization results of different batteries.

| Economic Indicators | VRB | Li-Con | NAS | VRLA |
| --- | --- | --- | --- | --- |
| net income/millions USD | 0.411 | 0.634 | 0.492 | 4.448 |
| total cost/millions USD | 0.770 | 1.499 | 1.591 | 1.010 |
| annual return/% | 7.64 | 6.3 | 3.42 | 6.43 |
| risk | High | Higher | Lower | Low |

In Table 4, the total net benefit of various energy storage systems—VRLA, NAS, Li-con, and VRB—exhibits significant differences due to variations in cost, risk, lifespan, and economic performance. Among them, VRB demonstrates the highest return on investment (annual return of 7.64%) and considerable economic benefit (net income of USD 0.411 million). However, its advantages are offset by its high operational risk, complex system configuration, and substantial space requirements, which may limit its practical applications. Li-con, despite having the highest total cost (USD 1.499 million), achieves the greatest net income (USD 0.634 million) due to its extended operational lifespan and stable performance across its lifecycle. Its competitive return on investment (annual return of 6.3%) can be attributed to its mature technology and widespread adoption in practical projects, though it entails higher operational risks. NAS, with its low risk, high power density, and long lifespan, offers stable economic performance in the later stages of its lifecycle. However, its total cost is the highest among the four systems (USD 1.591 million), resulting in a relatively low return on investment (annual return of 3.42%) and limiting its overall economic attractiveness in the current market. VRLA stands out for its low investment cost (USD 1.010 million) and relatively high short-term returns (net income of USD 4.448 million). However, its shorter lifespan restricts its economic performance over the full lifecycle. While it provides a competitive annual return of 6.43%, its benefits diminish as reinvestment becomes necessary, making it more suitable for short-term or low-cost applications.

**Table 5.** Battery configuration under different risk factors.

| L | Parameter | VRB | Li-Con | NAS | VRLA |
|---|---|---|---|---|---|
| 0.05 | Power/MW | 14.2 | 5.8 | 4.2 | 3.6 |
| | Capacity/MW·h | 92.2 | 36 | 24.4 | 28 |
| 0.2 | Power/MW | 13.2 | 3.6 | 6.2 | 4.8 |
| | Capacity/MW·h | 84.4 | 28.4 | 36 | 37.4 |
| 0.8 | Power/MW | 10.4 | 1.4 | 8.4 | 7.6 |
| | Capacity/MW·h | 66.4 | 14.6 | 48.8 | 56.4 |
| 1.5 | Power/MW | 9.4 | 0.8 | 11.2 | 8.4 |
| | Capacity/MW·h | 47.2 | 12.2 | 65 | 77.2 |

Among the economic indicators, the daily average photovoltaic output and market transactions during the operation of these power storage systems serve as primary measures of operational risk. The variability and intermittency of photovoltaic output pose operational imbalances, while increased market transaction volumes elevate the risk of tie-line congestion, potentially jeopardizing the safe and stable operation of the power grid. Thus, market transaction volume and photovoltaic output reflect the operational risk of these batteries. Based on this indicator, the operational risks of VRLA, NAS, Li-con, and VRB decrease, with VRB exhibiting higher yields but also facing greater safety risks.

### 3.2.2. The Impact of Different Risk Factors on User-Side Energy Storage Configuration

The hybrid algorithm proposed in this article is programmed and solved using GAMS software. The configuration of each battery under different risk coefficients is shown in Table 5.

The table illustrates that the variations in battery output power and configuration capacity follow similar patterns. When the risk is minimal and investment strategies lean towards aggressiveness, VRLA and NAS configurations exhibit lower power and corresponding capacity. Conversely, during such periods, VRB configurations demonstrate relatively higher power and capacity. As the risk coefficient escalates and investment strategies trend towards conservatism, VRLA and NAS configurations are characterized by higher output power and larger battery capacities. Consequently, VRB configurations exhibit lower power and capacity. Moreover, owing to the modest annual return on investment of Li-con and the comparatively lower initial investment and construction costs for large-scale applications, the utilization of Li-con batteries remains minimal across the various risk types.

Figures 5 and 6 show the power configuration, photovoltaic output, and market power purchase of various types of batteries under different risk factors.

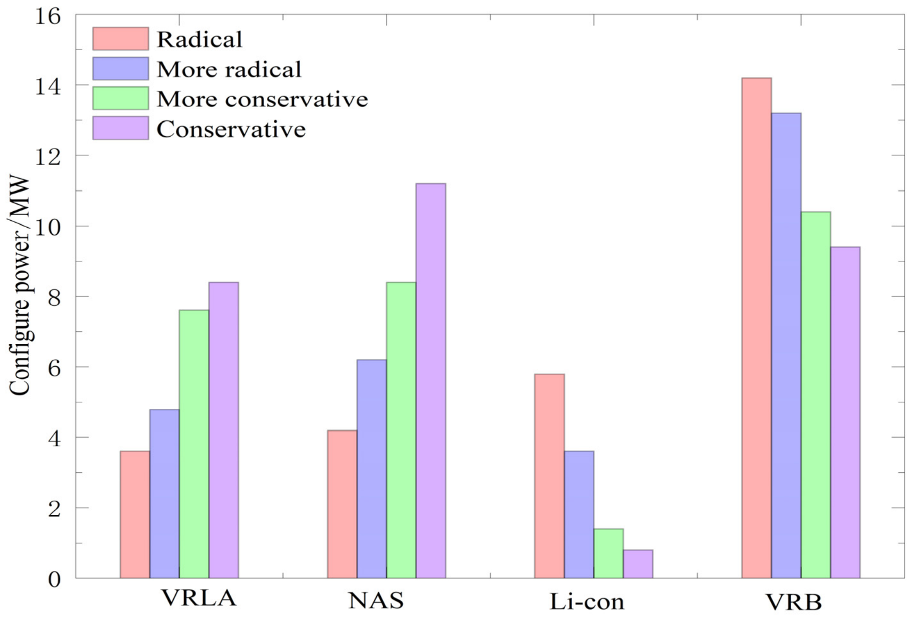


**Figure 5.** Configuration scheme of each battery.

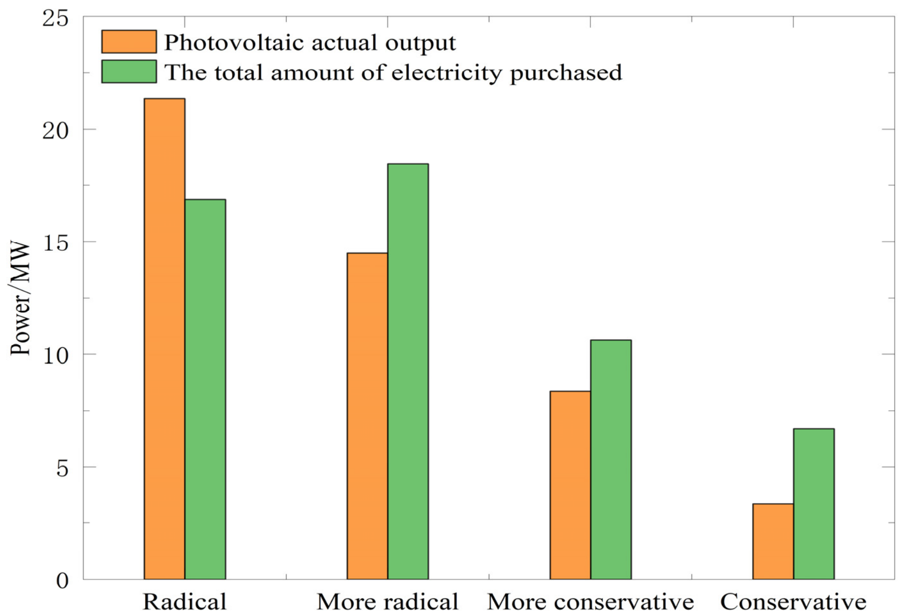


**Figure 6.** PV output and power purchase.

Figures 5 and 6 show that investors are willing to take higher risks for higher returns when the risk factor is low. In this scenario, with better returns and higher operational risks, VRB and Li-con become the main batteries in the configuration scheme. Due to the performance risk and volatility of PV output, it is important to carefully consider battery selection. Under this scheme, the source charge often experiences an imbalance, requiring the purchase of additional power from the market to maintain a balance between supply and demand. As a result, the daily PV output and the amount of power purchased from the market are both high. On the other hand, as the risk factor increases and the investment strategy becomes more conservative, VRLA and NAS batteries become the main power sources due to their maturity. The reliable charging and discharging of the batteries, along with lower PV output and market-traded power, improve the source–load balance under this scenario, resulting in lower operational risk.

Under different risk coefficients, the effective frontier curve of the income from the allocation plan and the conditional risk value are shown in Figure 7:

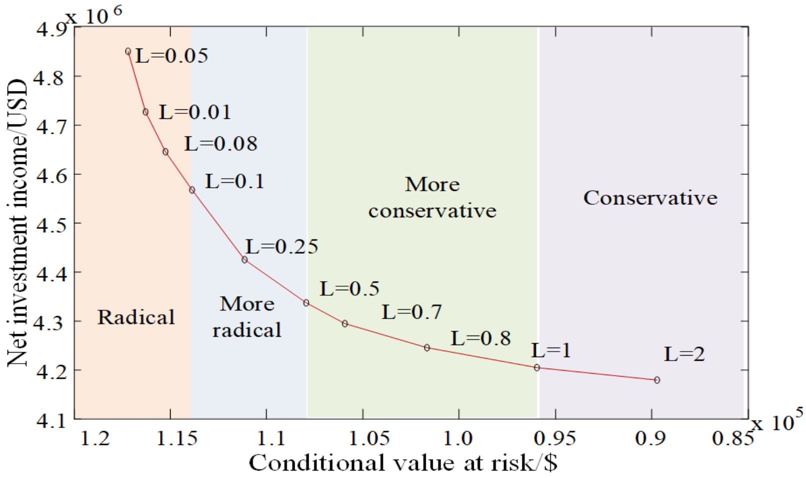


**Figure 7.** Effective frontier curve of benefit and conditional risk value of allocation scheme.

Figure 7 reveals a clear relationship between the risk coefficient, conditional risk value, and the total return of the allocation strategy. When the risk coefficient is low, the investment strategy adopts a more aggressive stance. In this scenario, investors are willing to accept higher levels of risk, leading to elevated conditional risk values. This increased risk tolerance is rewarded with higher total returns, as the allocation strategy prioritizes high-reward opportunities that inherently carry greater uncertainties. As the risk coefficient increases, the investment strategy transitions to a more conservative approach. Investors aim to minimize exposure to potential losses, resulting in a gradual reduction in the conditional risk value. Correspondingly, the total return of the system decreases, albeit at a slower rate. This reflects a trade-off where lower risk tolerance leads to diminished investment returns but offers greater stability and reduced exposure to extreme losses.

Overall, the results underscore that the trend of the conditional risk value and the total return of the allocation strategy are aligned. A higher conditional risk value corresponds to a higher return, while a lower conditional risk value is associated with more modest returns. This relationship highlights the importance of risk preferences in shaping energy storage investment strategies, providing investors with a framework to balance potential returns against acceptable risk levels.

## 4. Conclusions

The document introduces a conditional CVaR model designed to optimize the allocation of energy storage on the user side by integrating a comprehensive assessment of costs, benefits, and operational uncertainties throughout the entire battery life cycle. This framework was developed to align with investor preferences, accommodating varying risk appetites to support decision-making in energy storage investments. Through illustrative analysis, the model's effectiveness was demonstrated, leading to the following conclusions.

Incorporating CVaR into energy storage strategies offers significant advantages by providing a detailed evaluation of risks and returns, particularly in the context of fluctuations in renewable energy availability and battery efficiency. The analysis highlights that different battery types exhibit distinct financial benefits and operational risks. For instance, vanadium redox flow (VRB) batteries are advantageous for investors with higher risk tolerance, as they deliver greater returns under fluctuating conditions, making them suitable for primary power configurations. Conversely, investors prioritizing risk mitigation tend to prefer sodium–sulfur (NAS) and valve-regulated lead–acid (VRLA) batteries, which offer greater stability and consistent performance in primary setups.

The CVaR method employed in this study was specifically designed to assess the influence of investors' risk preferences on energy storage system configurations. Unlike conventional approaches that primarily emphasize optimizing technical or operational performance, this method prioritizes addressing risk-based decision-making challenges under uncertainty. Each methodology offers unique advantages and limitations, depending on its specific objectives and underlying assumptions. Future research could focus on benchmarking the CVaR method against alternative approaches under comparable conditions to provide a more comprehensive evaluation of its strengths and limitations.

This study further notes that various battery types possess unique characteristics, including differences in operational metrics, costs, and configurations, complicating the development of a standardized model for battery life degradation. This research does not directly address the impact of battery aging on operational efficiency, an area requiring further investigation. Future studies aim to develop a unified model for battery life deterioration, enabling a more detailed evaluation of the effects of aging on performance and design outcomes. Such advancements would enhance the precision and applicability of the proposed model, improving its ability to guide strategic investments in energy storage over time.

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