

Article

Optimization of a Nuclear–CSP Hybrid Energy System Through Multi-Objective Evolutionary Algorithms

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Abstract: Combining energy storage with base-load power sources offers an effective way to cover the fluctuation of renewable energy. This study proposes a nuclear–solar hybrid energy system (NSHES), which integrates a small modular thorium molten salt reactor (smTMSR), concentrating solar power (CSP), and thermal energy storage (TES). Two operation modes are designed and analyzed: constant nuclear power (mode 1) and adjusted nuclear power (mode 2). The nondominated sorting genetic algorithm II (NSGA-II) is applied to minimize both the deficiency of power supply probability (DPSP) and the levelized cost of energy (LCOE). The decision variables used are the solar multiple (SM) of CSP and the theoretical storage duration (TSD) of TES. The criteria importance through inter-criteria correlation (CRITIC) method and the technique for order preference by similarity to ideal solution (TOPSIS) are utilized to derive the optimal compromise solution. The electricity curtailment probability (ECP) is calculated, and the results show that mode 2 has a lower ECP compared with mode 1. Furthermore, the configuration with an installed capacity of nuclear and CSP (100:100) has the lowest LCOE and ECP when the DPSP is satisfied with certain conditions. Optimizing the NSHES offers an effective approach to mitigating the mismatch between energy supply and demand.

Keywords: nuclear and solar hybrid energy system; multi-objective optimization; concentrating solar power; thermal energy storage; levelized cost of electricity; solar multiple



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1. Introduction

Driven by the rapid advancement of the global economy and society, worldwide energy consumption has continued to rise. The global consumption of fossil fuels, primarily including coal, oil, and natural gas, is projected to peak by 2030, with oil and natural gas usage remaining at elevated levels over the next three decades [1]. To mitigate energy and environmental crises, optimize the energy structure, and ensure energy security, the global community is intensifying efforts to advance clean and renewable energy technologies. The large-scale integration of renewable energy, mainly wind and solar, leads to intermittent fluctuations over various time scales, presenting significant challenges for grid management [2]. The rapid increase in the penetration rate of renewable energy leads to negative electricity prices, requiring significant changes in the traditional energy systems [3]. From the perspective of capital investment, as well as the operation and maintenance (O&M) of facilities, this poses challenges for base-load power plants. Therefore, the world needs to harness renewable energy in a more reliable, efficient, and cost-effective manner.

Currently, concentrating solar power (CSP) benefits from the application of molten salt thermal storage technology, achieving continuous power generation 24 h a day [4]. However, constrained by seasonal sunlight conditions, CSP cannot maintain continuous operation throughout the year. Continuously increasing the scale of the thermal storage system cannot completely solve the problem and may instead lead to an increase in electricity costs [5]. Introducing one or more mature base-load energy technologies as supplementary sources to form a hybrid energy generation system can enhance continuous power generation capabilities and reduce power generation costs [6]. Nuclear energy, with its high energy density, stability, and resilience, presents a promising option for base-load power alongside renewable energy. In the field of nuclear energy technology, small modular molten salt reactors belong to the fourth generation of reactors. This reactor design offers high efficiency and safety (high temperature, low pressure, and stable) with flexible and economic deployment (low cost, fast build, and easy O&M), facilitating long-lasting clean energy deployment. Therefore, it has emerged as a potential candidate for integration with renewable energy to create a hybrid energy system at the current stage [7]. The coupling between solar heat energy and nuclear energy is achieved through thermal coupling, which is more closely integrated than other combinations of nuclear energy with renewable sources like wind and photovoltaic, allowing for lower coupling costs through a higher proportion of steam heat exchange and power generation system equipment [8]. In this context, the thermal energy storage (TES) system is crucial for balancing energy supply and demand, ensuring efficient energy dispatch to meet fluctuating demands. Numerous studies have focused on enhancing the performance of TES systems [9–11].

The integration of nuclear and renewable energy sources has been extensively examined by researchers as a synergistic approach to mitigating the inherent variability in renewable energy production while ensuring a stable and consistent supply of electricity to meet grid demand. In 2014, Ruth et al. [12] introduced a conceptual design for a nuclear hybrid energy system, with nuclear energy serving as the baseload. This system features a thermal energy storage-dominated management system, complemented by electrical and hydrogen storage, and supports multiple clean energy inputs and applications, such as power generation, heating, liquid fuel synthesis, and desalination. Subsequent studies based on this conceptual design explored different configurations and optimizations. For instance, Popov et al. [13] developed a nuclear–solar hybrid energy system that enhanced thermal-to-power conversion efficiency but failed to address the intermittency of solar thermal power generation. Wang et al. [14] made significant contributions through their investigation of an innovative hybrid configuration, integrating a hybrid system combining a small lead-cooled fast reactor with solar energy utilizing a supercritical CO₂ Brayton cycle, demonstrating that the proposed hybrid system increased power generation. Optimization efforts have also focused on improving system efficiency and reducing the environmental impact. Naserbegi et al. [15] conducted an optimization study on a nuclear–solar hybrid power plant coupled with a desalination system, increasing electrical efficiency from 27.03% to 30.18% while significantly reducing CO₂ emissions. Meanwhile, Son et al. [16] explored the feasibility of a hybrid system integrating a micro modular reactor, CSP, and TES for distributed power applications, showing that such systems can mitigate the intermittency of solar thermal power by increasing the reactor’s capacity. Most recently, Zhao et al. [17] presented three integration schemes for coupling CSP with nuclear power plants and assessed their performance in terms of energy efficiency. Numerical results revealed that utilizing solar energy to preheat feedwater and saturated steam is the most efficient method for enhancing the overall thermal efficiency of the hybrid system.

The optimization of hybrid systems primarily focuses on enhancing the economic viability, reliability, and efficiency of renewable energy systems through advanced optimiza-

tion algorithms and models, taking into account factors such as electrical load variation, uncertainty, and multi-timescale characteristics. Sharafi et al. [18] introduced a method employing the dynamic multi-objective particle swarm optimization algorithm to optimize hybrid renewable energy systems, with objectives to minimize the total net present value cost, maximize the share of renewable energy, and reduce fuel emissions. Fares et al. [19] employed ten optimization algorithms, including GA, cuckoo search, simulated annealing, etc., to optimize the sizing of standalone hybrid renewable energy systems comprising photovoltaic (PV), wind turbines (WT), and batteries. The robustness, accuracy, and computational time of different optimization algorithms were compared. He et al. [20] performed capacity optimization for wind–solar hybrid systems, integrating various energy storage technologies, including batteries, thermal energy storage (TES), pumped hydro storage, and hydrogen storage, while a comprehensive metric method based on the hypervolume measure was employed to evaluate the performance of four distinct algorithms: the non-dominated sorting genetic algorithm (NSGA-II), the multi-objective evolutionary algorithm based on decomposition, multi-objective particle swarm optimization (MOPSO), and the strength Pareto evolutionary algorithm. Abuelrub et al. [21] integrated the biogeography-based optimization algorithm with the particle swarm optimization algorithm to develop a novel optimization approach for minimizing system costs and enhancing the reliability of WT–PV hybrid energy systems. The results demonstrated that, in comparison to NSGA-II and MOPSO, the proposed algorithm notably improved search efficiency in identifying the optimal system configuration.

However, within the framework of multi-objective optimization problems, inherent conflicts among objectives often prevent the simultaneous attainment of optimal solutions for all targets. Instead, these optimization processes typically yield a set of Pareto-optimal or non-dominated solutions, where improvement in one objective necessitates a compromise in at least one other objective. Consequently, a trade-off analysis must be conducted to identify the optimal compromise solution that best balances the competing objectives based on specific criteria or preferences. Multi-criteria decision-making (MCDM) techniques are extensively employed to identify the most appropriate solutions by assessing alternatives against a range of criteria. Compared to other methods for determining indicator weights, such as the entropy method, principal component analysis, and the coefficient of variation, the criteria importance through the inter-criteria correlation (CRITIC) method offers a distinct advantage. It takes into account both the variability and intercorrelation within the Pareto-optimal solution set to assign weights [22]. The technique for order preference by similarity to ideal solution (TOPSIS) [23], proposed as early as 1981, remains one of the most established approaches for addressing multi-attribute decision-making (MADM) problems. Compared to other ranking techniques such as Visekriterijumsko Kompromisno Rangiranje (VIKOR), the preference ranking organization method for enrichment evaluations (PROMETHEE), and ELECTRE, TOPSIS is widely valued for its methodological simplicity and practical applicability [24]. Nie et al. [25] used multi-objective evolutionary algorithms (MOEAs) in conjunction with the CRITIC-TOPSIS method, the optimal operational mode was identified, and the optimal capacity configuration of the nuclear–renewable hybrid energy system was identified, with the overarching goal of effectively meeting the energy demands of the community. In conclusion, the integration of MOEAs with the MCDM approach, specifically CRITIC-TOPSIS, proves to be a highly effective methodology for optimizing the configuration of hybrid energy systems.

Advanced artificial intelligence algorithms have been widely developed and implemented for the optimization of hybrid energy systems. However, research on the optimization of nuclear–solar hybrid energy systems (NSHES) that simultaneously considers both cost and power supply stability remains limited. In the present study, a methodology

combining MOEAs with the CRITIC-TOPSIS approach is utilized to identify the optimal configuration of the NSHES, aiming to satisfy the load of community requirements.

2. Methodology

2.1. Description of the NSHES

The NSHES is an integrated system that dynamically allocates thermal energy to ensure responsive and reliable power generation for the grid. This section outlines the comprehensive configuration and operational strategy of this hybrid energy system. This paper refers to a system structure that uses large-scale heat storage at the level of hundreds of megawatts or even gigawatts to separate the nuclear heat system and solar heat collection system from the thermal-to-work conversion system, ensuring that the small modular reactor operates at base load and reducing the system investment cost [26]. The schematic configuration of the proposed NSHES is shown in Figure 1. The hybrid system is composed of four main subsystems: a nuclear heat generation unit, a CSP heat generation unit, a thermal energy storage and dispatch system, and a power generation system.

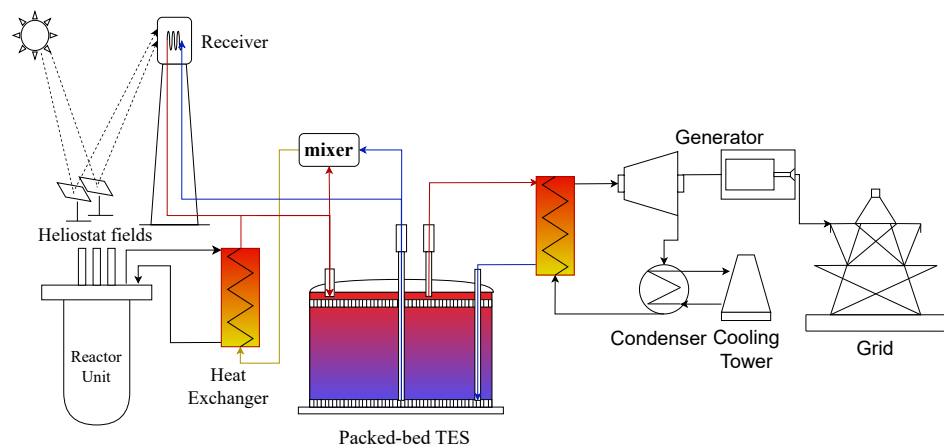


Figure 1. Schematic configuration of the NSHES [27].

The nuclear heat generation system consists of one or more 20 MW_e small modular thorium molten salt reactors (smTMSR). The smTMSR contains a primary circuit (fuel salt: NaF – BeF₂ or LiF – BeF₂) and a secondary circuit (coolant salt: NaF – BeF₂). The coolant salt circuit couples with the CSP heat generation system and packed-bed thermal energy storage (PB-TES) by the heat exchanger in NSHES. The CSP heat generation system mainly consists of heliostat fields, a receiver, and a tower. The receiver transforms solar radiation, which is captured and concentrated by a heliostat field, into thermal energy using solar salt. The thermal energy storage and dispatch system comprises a molten-salt mixer and PB-TES. The mixer ensures the inlet temperatures of the secondary heat exchanger of smTMSR meet the requirements by mixing the heated HTF of the CSP and the cold HTF of PB-TES. The PB-TES includes a stationary packed bed for solid-phase thermal storage and solar salt for liquid-phase thermal storage, operating as a dual-medium low-pressure thermal energy system [28]. The power generation system is based on the design of the Crescent Dunes project, utilizing a sub-critical Rankine cycle steam turbine with a regenerative system as the power block (PB) [29]. The PB offers advantages such as quick start-ups, frequent cycling, and flexible output regulation. In this study, the PB is simplified and not subjected to in-depth analysis.

In this hybrid system, both the nuclear heat generation system and the CSP heat generation system utilize solar salt to deliver thermal energy to the TES. In the thermal energy storage and dispatch system, two molten salt pumps are utilized to facilitate the

circulation of the HTF, enabling both the charging and discharging processes. In the PB-TES charging mode, the low-temperature pump transports the cold HTF from the bottom of the storage tank to the mixer and the solar heat collection system. A portion of the cold HTF is blended from the solar heat generation system to maintain the desired inlet temperature of the secondary circuit heat exchanger; the other part of the cold HTF is pumped through the solar receiver on the top of the central tower and heated to the inlet temperature of the PB-TES. The process halts once the HTF reaches the designated charging cut-off temperature of the PB-TES. In the PB-TES discharge mode, the hot HTF is extracted from the top of the storage tank by the high-temperature pump and flows back to the bottom of the storage tank after finishing the heat exchange with PB through the heat exchanger. When the heat generated by the reactor core and CSP matches the thermal energy demand of the PB, the PB-TES will enter standby mode.

Two operation modes of the NSHES are considered: nuclear power is kept in full load operation (mode 1), and nuclear power adjusts with the thermal state and operation mode of PB-TES (mode 2). In mode 2, when the load factor (LF is the ratio of currently available stored thermal energy to the theoretical maximum capacity) of PB-TES rises above 85% (a designated value indicating that the PB-TES is approaching full charge), smTMSRs operate at reduced power levels, designed to independently satisfy the thermal load requirements of the minimum grid demand. The LF is defined as the ratio of the currently available stored thermal energy to the theoretical maximum storage capacity. The smTMSRs return to full-load operation under the following conditions: (1) the duration of reduced heat generation from the smTMSR exceeds 3 h, and (2) the LF of the PB-TES falls to a level where heat generation cannot be reduced within the subsequent 3 h. Both operation modes operate with the same calculation scheme, as shown in Figure 2. During the advancement of the time step, the real-time nuclear thermal power, CSP receiver thermal power, and grid load are provided as inputs. The real-time nuclear thermal power in mode 1 remains constant, and in mode 2, it is adjusted. Then, the actual total heat generation $P_{th,tolG}$ and planned thermal load of PB $P_{th,PB,pl}$ are calculated. When $P_{th,tolG}$ is greater than $P_{th,PB,pl}$, PB-TES will be charged. When $P_{th,tolG}$ is less than $P_{th,PB,pl}$, PB-TES will be discharged. When $P_{th,tolG}$ is equal to $P_{th,PB,pl}$, PB-TES will be on standby. Next, the LF of PB-TES and the actual power generation of the system $P_{e,PB,act}$ are calculated. Finally, verify if the running time has reached the specified simulation duration.

2.2. Mathematical Models

2.2.1. Small Modular Reactor Model

The Chinese Academy of Sciences launched the “Thorium Molten Salt Reactor Nuclear Energy System” project to improve the efficient use of thorium. In the first step of this project, the Shanghai Institute of Applied Physics proposed a 2 MW_{th} liquid-fueled molten salt reactor [30]. A 20 MW_e smTMSR, along with its accompanying scientific infrastructure, is under design and slated for future construction. In this study, the smTMSR is regarded as the primary energy source, operating at a stable thermal output to ensure both economic efficiency and operational safety. The thermal power output of the smTMSR is calculated as follows:

$$P_{th,smTMSR} = \int_V \Phi \cdot \Sigma_f \cdot E_f dV, \quad (1)$$

where $P_{th,smTMSR}$ is the thermal power of the smTMSR, ϕ is the neutron flux, Σ_f is the macroscopic fission cross-section, V is the volume of the reactor core, and E_f is the energy released per fission event.

2.2.2. CSP Heat Generation System Model

Solar towers are particularly well-suited for hybrid power generation with other energy sources due to their high concentration ratios and extensive operational temperature range. In this paper, the CSP heat generation system refers to the design of a 100 MW_e CSP [31]. The receiver is installed at the top of the tower, and a suitable number of heliostats are distributed around the tower. The heliostat field is managed by an automated computer system that ensures precise sunlight tracking. The reflected sunlight is directed to the receiver, where it heats the molten salt heat transfer medium, effectively converting solar energy into usable thermal energy. There are various arrangements for the heliostat field layout, including a radial staggered layout, a cornfield layout, a biomimetic layout, a north-facing layout, and a surrounding heliostat field layout. The factors considered in the layout include shading and occlusion, cosine losses, intercept efficiency, mirror reflectance, dust factors, latitude, wind speed, and site layout.

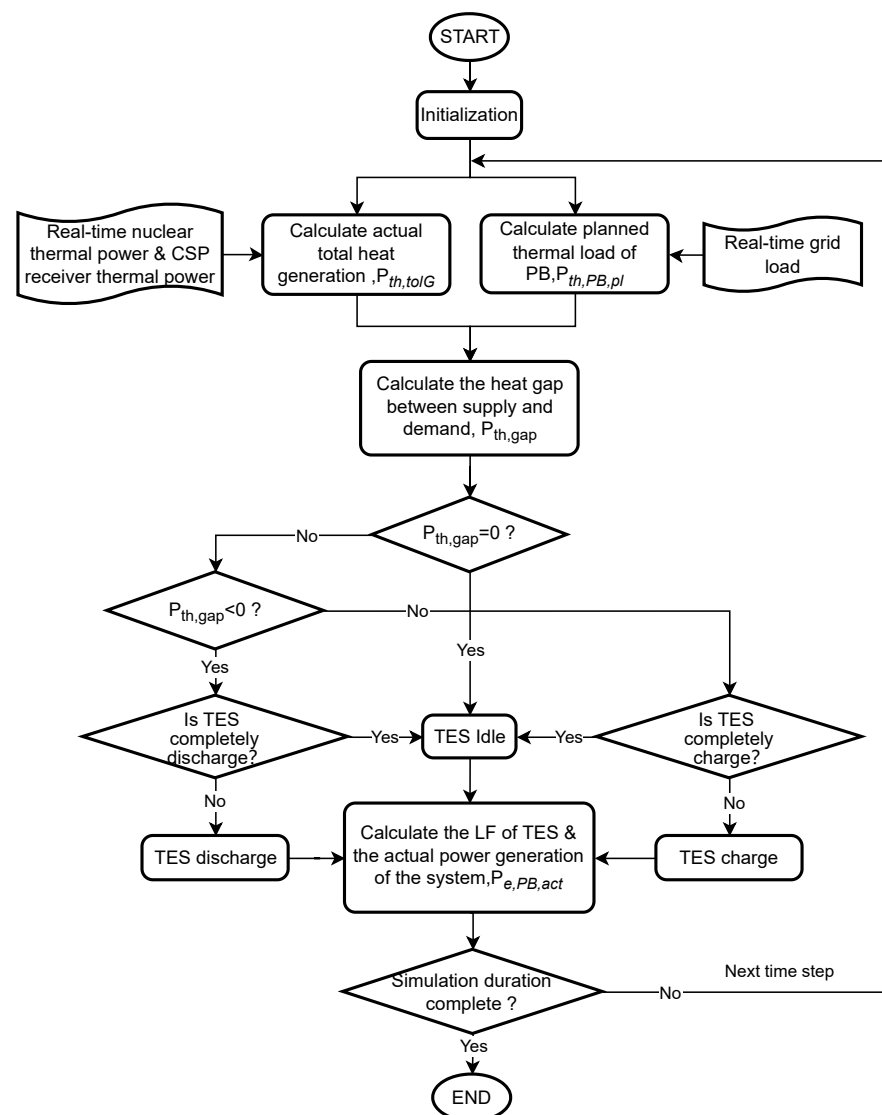


Figure 2. Calculation scheme for the NSHES.

The total heat collected by the heliostat field can be calculated using the following equation:

$$Q_{solarfield} = DNI \cdot A_{hel} \cdot \eta_{col}, \quad (2)$$

$$Q_{rec,r} = \eta_{rec} \cdot Q_{solarfield}, \quad (3)$$

where $Q_{solar\,field}$ is the heat collected by the heliostat field, DNI is the direct normal irradiance, A_{hel} is the total reflective area of the mirror field, η_{col} is the total collection efficiency of the mirror field, $Q_{rec,r}$ is the total heat generated by the receiver, and η_{rec} is the total thermal collection efficiency of the receiver. The total collection efficiency of the mirror field is influenced by cosine efficiency, optical efficiency, atmospheric cleanliness, optical errors, etc.

To accurately obtain the solar energy collection power under solar irradiance conditions, the 100 MW_e molten salt tower CSP heat generation system is modeled using the open-source software, System Advisor Model (SAM). The version used is SAM 2023.12.17 for Windows. This software, developed by the National Renewable Energy Laboratory (NREL), serves as a comprehensive and flexible platform for modeling and analyzing renewable energy systems [32]. It is designed to assist engineers, researchers, and policymakers in the design, evaluation, and optimization of renewable energy projects.

The SAM modeling process typically involves several key steps:

1. Project definition and setup, including selecting the energy technology (CSP, PV, WT, and TES), specifying the project location based on weather data, and configuring the system's capacity;
2. Preparing input data, such as meteorological data, equipment parameters, and load profiles;
3. System design and configuration, covering the physical layout, electrical connections, and storage system setup;
4. Running simulations by defining the time range, setting operational parameters, and executing the model to calculate performance metrics like energy generation and efficiency;
5. Analyzing results and optimizing the system through performance evaluation, sensitivity analysis, and design adjustments;
6. Generating reports with visual outputs and detailed analysis for decision-making.

By entering the designed parameters of the CSP heat generation system and local weather data, SAM can precisely simulate and compute the thermal power output, electrical generation, and related expenses of solar thermal power plants [32]. The distribution of the heliostat field in the CSP heat generation system model is shown in Figure 3, with the following design parameters: the direct normal irradiance (DNI) design value is 900 W/m², the solar multiple is 2.4, and the tower height is 240 m in Wuwei County, Gansu Province, China.

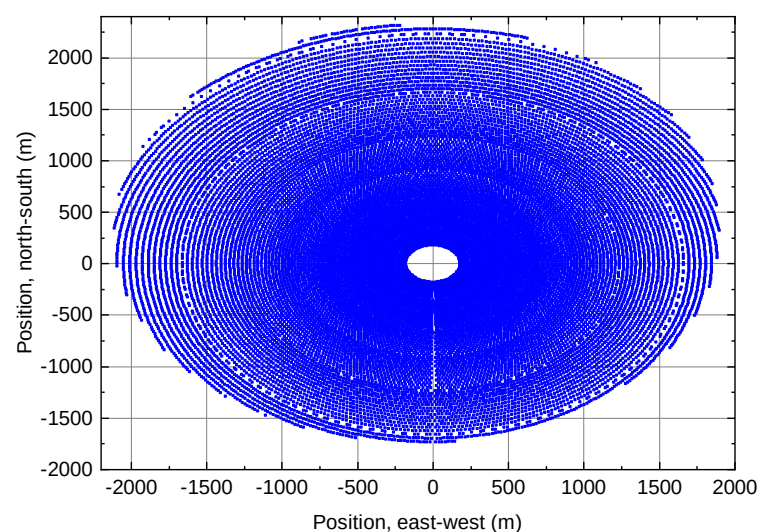


Figure 3. Schematic diagram of heliostat field distribution.

2.2.3. Packed-Bed Thermal Energy Storage Model

The PB-TES system is utilized to store excess thermal energy produced by both the nuclear reactor and the CSP unit. The mathematical model describing the TES system is formulated as follows [33]:

$$Q_{TES,tot}(t) = Q_{TES,tot}(t-1)(1 - \sigma_{TES}) + (P_{TES,c})\eta_{TES,c} \times \Delta t, \quad (4)$$

$$Q_{TES,tot}(t) = Q_{TES,tot}(t-1)(1 - \sigma_{TES}) - \frac{(P_{TES,dis})}{\eta_{TES,dis}} \times \Delta t, \quad (5)$$

where $Q_{TES,tot}(t)$ and $Q_{TES,tot}(t-1)$ are the total thermal energy stored in the TES at time t and $t-1$. $P_{TES,c}$ and $P_{TES,dis}$ represents the charging and discharging power of the TES, respectively. $\eta_{TES,c}$ and $\eta_{TES,dis}$ denote the charging and discharging efficiencies, and σ_{TES} corresponds to the heat loss rate of the TES system.

3. Optimization Method

In the configuration optimization of the NSHES, multi-objective optimization is employed to generate a set of Pareto-optimal solutions, whereas MCDM techniques are utilized to identify the most favorable solution from among the Pareto solutions. In this study, NSGA-II is applied in the NSHES model to obtain Pareto solutions, considering the decision variables, optimization objectives, and constraints conditions. The optimization framework is described in Figure 4.

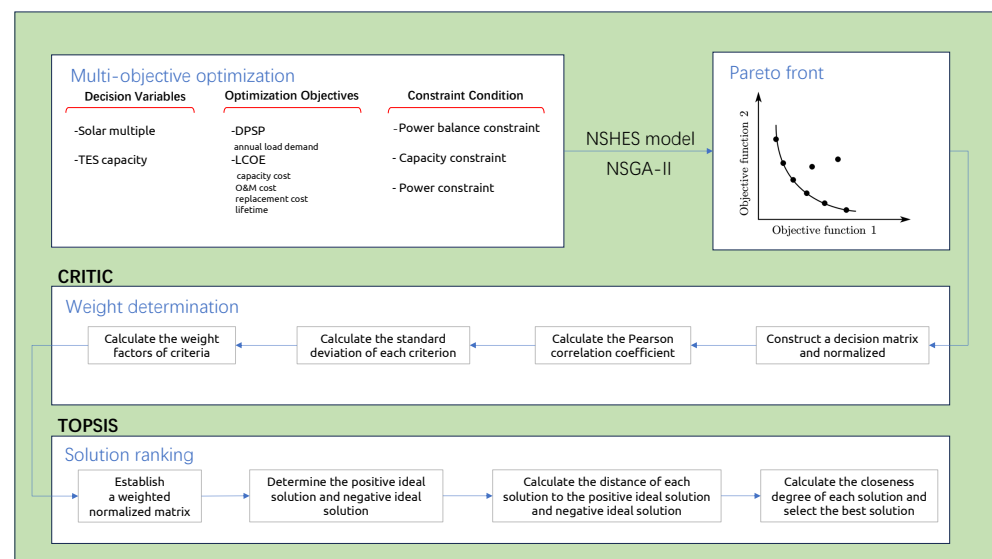


Figure 4. Optimization framework for the NSHES.

3.1. Decision Variables

In this optimization problem, the decision variables include the number of smTMSRs, the solar multiple (SM), and the TES capacity. The SM and TES capacity are described as follows.

3.1.1. Solar Multiple

The SM is an important design parameter for optimizing the CSP configuration and ensuring the power block operates effectively over a year [13]:

$$SM = \frac{Q_{solar\ field}}{Q_{PB}}, \quad (6)$$

where the Q_{PB} is the sum of thermal energy required for the PB.

3.1.2. TES Capacity

The theoretical storage duration (TSD) quantifies the energy storage capacity of the PB-TES, which is mathematically expressed as follows:

$$TSD = \frac{Q_{TES,MAX}}{P_{pb,r}}, \quad (7)$$

where $Q_{TES,MAX}$ denotes the theoretical maximum storage capacity of the PB-TES, and $P_{pb,r}$ denotes the rated charge or discharge power of the PB-TES.

3.2. Optimization Objectives

The optimization objectives include the levelized cost of energy (LCOE) and the deficiency of power supply probability (DPSP). A detailed description of these objectives is provided below.

3.2.1. Deficiency of Power Supply Probability

The DPSP is utilized to assess and guarantee the reliability of the power supply of a hybrid energy system. It is calculated as the ratio of the total power deficiency to the grid load over a year. The DPSP ranges from 0 to 1, with lower values signifying greater reliability in the system's power supply. Its definition is as follows:

$$DPSP = \frac{\sum_0^T DPS(t)}{\sum_0^T E_{load}(t)}, \quad (8)$$

$$DPS(t) = E_{load}(t) - P_{e,PB,act}(t), \quad (9)$$

where $DPS(t)$ is the deficiency of the power supply at time t , E_{load} is the electrical power of the grid load, and $P_{e,PB,act}$ is the electrical power output of the PB.

3.2.2. Levelized Cost of Energy

The levelized cost of energy (LCOE) quantifies the average cost per kilowatt-hour of usable electricity generated by the system throughout its operational lifetime, including construction, O&M, and fuel costs (if relevant). This paper adapts LCOE calculation methods for CSP and nuclear power plants to derive a suitable approach for the NSHES. The specific derivation process is as follows.

The LCOE is the unit cost of electricity generated by the nuclear, renewable hybrid energy system over its design life [34]:

$$LCOE = \frac{TNPC \cdot CRF}{E}, \quad (10)$$

where $TNPC$ is the total net present cost over the project lifecycle, CRF is the capital recovery factor, and E is the total electrical energy produced over its lifetime. $TNPC$ and CRF can be calculated using the following equations [35,36]:

$$TNPC = NPC_{smTMSR} + NPC_{sol} + NPC_{TES} + NPC_{PB}, \quad (11)$$

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1}, \quad (12)$$

$$i = \frac{i - f}{1 + f}, \quad (13)$$

where NPC_{smTMSR} , NPC_{sol} , NPC_{TES} , and NPC_{PB} are the net present costs of the smTMSR, the CSP heat generation system, the PB-TES, and the power generation system. i is the real

discount rate, n is the total lifecycle of the hybrid energy system, i is the nominal discount rate, and f is the inflation rate.

The NPC_{smTMSR} is calculated using the following equation [25]:

$$NPC_{smTMSR} = SMR_{cap} + \frac{(SMR_{FOM} + SMR_{VOM} + SMR_{FC})}{CRF} + \frac{SMR_{decom}}{(1+i)^k}, \quad (14)$$

where SMR_{cap} denotes the overnight capital cost of the smTMSR, SMR_{FOM} represents the annual fixed O&M cost, SMR_{VOM} is the annual variable O&M cost, SMR_{FC} corresponds to the fuel cost, SMR_{decom} indicates the decommissioning cost, and k refers to the operational lifetime of the smTMSR.

The NPC_{sol} is calculated using the following equation [37]:

$$NPC_{sol} = \left(\frac{k_d(1+k_d)^n}{(1+k_d)^n - 1} + k_{insurance} \right) \frac{C_{sol, cap}}{CRF} + \frac{C_{sol, O\&M}}{CRF}, \quad (15)$$

$$C_{sol, cap} = C_{hel, cap} + C_{tow, cap} + C_{rec, cap}, \quad (16)$$

where k_d is the actual debt interest of the CSP, $k_{insurance}$ is the annual insurance premium rate of the CSP, $C_{sol, cap}$ is the construction cost of the CSP, and $C_{sol, O\&M}$ is the annual O&M cost of the CSP. $C_{hel, cap}$ is the investment cost of the heliostat field, $C_{tow, cap}$ is the investment cost of the tower, and $C_{rec, cap}$ is the investment cost of the receiver.

The NPC_{TES} and NPC_{PB} can be calculated using the following equation:

$$NPC_i = Cap_i + \frac{O\&M_i}{CRF}, \quad (17)$$

where Cap_i is the capital cost of the system's components, and $O\&M_i$ is the annual O&M cost of the system's components.

3.2.3. Constraints Conditions

The power balance constraints are expressed as follows:

$$P_{load} - P_{DPS} = (P_{th, smTMSR} + P_{rec} + P_{TES}) \cdot \eta_{PB}, \quad (18)$$

where P_{DPS} is the DPS, P_{rec} is the thermal power of the receiver, P_{TES} is the thermal energy power of the PB-TES, and η_{PB} is the thermal efficiency of the PB.

The total heat storage capacity and charging (or discharging) power of the TES satisfy the following constraints:

$$Q_{TES, min} \leq Q_{TES, tot} \leq Q_{TES, max}, \quad (19)$$

$$P_{TES, min} \leq P_{TES, tot} \leq P_{TES, max}, \quad (20)$$

where $Q_{TES, min}$ and $Q_{TES, max}$ are the minimum and maximum thermal storage capacities of the TES, and $Q_{TES, min}$ and $Q_{TES, max}$ are the minimum and maximum thermal charging (or discharging) power of the TES.

3.3. Non-Dominated Sorting Genetic Algorithm

The NSGA-II is an algorithm designed to address multi-objective optimization problems. This algorithm demonstrates superior exploratory capabilities while effectively mitigating premature convergence to local optima. Through adaptive non-dominated sorting, it selectively preserves elite individuals along the Pareto front, thereby enhancing the convergence efficiency and accelerating Pareto-optimal advancement without compromising computational tractability [24]. Typically, a multi-objective genetic algorithm

encompasses (1) the concept of solution dominance in multi-objective problems, (2) the identification of Pareto solution sets and the Pareto front, and (3) the use of genetic algorithms to seek global optimal solutions.

The population is initialized and obtains the parent population P_t , and then the offspring population Q_t is obtained by crossover and mutation of the parent population. Then, the parent and offspring populations are merged into R_t . Non-dominated sorting is then applied to R_t to select individuals for the next parent population P_{t+1} based on rank. If the population number exceeds the population size limit, individuals are selected based on descending crowding distance until P_{t+1} reaches size N . The aforementioned steps are iteratively executed following initialization until the predefined termination criterion is satisfied.

3.4. Multi-Criteria Decision Making

3.4.1. Criteria Importance Through the Inter-criteria Correlation Method

In the CRITIC method, the standard deviation is applied to quantify the degree of dispersion, while the Pearson correlation coefficient is used to quantify correlation. The main calculation steps of CRITIC are as follows [23]:

1. A decision matrix, denoted as A , is constructed with m rows representing the set of alternatives and n columns corresponding to the criteria. Then, the data are normalized to obtain a normalized matrix. For beneficial criteria (larger values indicate better outcomes) and non-beneficial criteria (smaller values indicate better outcomes), the decision matrix elements are normalized as follows:

$$x_{ij}^+ = \frac{a_{ij} - a_{j\min}}{a_{j\max} - a_{j\min}}; \quad i = 1, \dots, m; j = 1, \dots, n \quad \text{if } j \in F^+, \quad (21)$$

$$x_{ij}^- = \frac{a_{j\max} - a_{ij}}{a_{j\max} - a_{j\min}}; \quad i = 1, \dots, m; j = 1, \dots, n \quad \text{if } j \in F^-, \quad (22)$$

where $a_{j\max} = \max(a_{1j}, a_{2j}, \dots, a_{mj})$ and $a_{j\min} = \min(a_{1j}, a_{2j}, \dots, a_{mj})$.

2. The Pearson correlation coefficient is calculated between two criteria, j and k :

$$r_{ij} = \frac{\sum_{x=1}^m (a_{ix} - \bar{a}_i)(a_{jx} - \bar{a}_j)}{\sqrt{\sum_{x=1}^m (a_{ix} - \bar{a}_i)^2 \sum_{x=1}^m (a_{jx} - \bar{a}_j)^2}}, \quad (23)$$

where $\bar{x}_i$ and $\bar{x}_j$ represent the mean of the j th and i th criteria as follows:

$$\bar{x}_i = \frac{\bar{x}_1 + \bar{x}_2 + \dots + \bar{x}_i}{m}, \quad (24)$$

$$\bar{x}_j = \frac{\bar{x}_1 + \bar{x}_2 + \dots + \bar{x}_j}{n}. \quad (25)$$

3. The standard deviation of each criterion is calculated as follows:

$$\sigma_j = \sqrt{\sum_{i=1}^m \frac{x_{ij} - \bar{x}_j}{n-1}}; \quad j = 1, \dots, n. \quad (26)$$

4. The weight factors of the criteria are calculated as follows:

$$w_j = \frac{\sigma_j \sum_{j=1}^m (1 - r_{ij})}{\sum_{j=1}^m (\sigma_j \sum_{j=1}^n (1 - r_{ij}))}; \quad j = 1, \dots, n. \quad (27)$$

3.4.2. Technique for Order Preference by Similarity to Ideal Solution

The fundamental principle of TOPSIS is to rank alternative solutions by evaluating their distances from the positive ideal solution and the negative ideal solution. Specifically, alternatives closer to the positive ideal solution and farther from the negative ideal solution are ranked more favorably, as they are considered to be more optimal and less suboptimal.

The main steps of the TOPSIS method are as follows [22]:

1. Establish a weighted normalized matrix, where the weight values are determined by CRITIC:

$$V_{ij} = v_{ij}y_{ij} = \begin{bmatrix} a_{11} \cdot w_1 & a_{12} \cdot w_2 & \cdots & a_{1n} \cdot w_j \\ a_{21} \cdot w_1 & a_{22} \cdot w_2 & \cdots & a_{2n} \cdot w_j \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} \cdot w_1 & a_{m2} \cdot w_2 & \cdots & a_{mn} \cdot w_j \end{bmatrix}. \quad (28)$$

2. Identify the positive ideal solution and the negative ideal solution, where F_1 is a set of beneficial criteria, F_2 is a set of non-beneficial criteria, and $j = 1, 2, \dots, n$.

$$z_j^+ = \begin{cases} \max_{1 \leq i \leq m}(v_{ij}) & \text{if } f_j \in F_1 \\ \min_{1 \leq i \leq m}(v_{ij}) & \text{if } f_j \in F_2 \end{cases}, \quad (29)$$

$$z_j^- = \begin{cases} \min_{1 \leq i \leq m}(v_{ij}) & \text{if } f_j \in F_1 \\ \max_{1 \leq i \leq m}(v_{ij}) & \text{if } f_j \in F_2 \end{cases}. \quad (30)$$

3. Calculate the distance of each solution to the positive ideal solution and negative ideal solution:

$$S_i^+ = \sum_{j=1}^n (v_{ij} - z_j^+)^2 \quad i = 1, 2, \dots, m, \quad (31)$$

$$S_i^- = \sum_{j=1}^n (v_{ij} - z_j^-)^2 \quad i = 1, 2, \dots, m. \quad (32)$$

4. Calculate the closeness degree of each solution to the ideal solution, where a higher value for C_i indicates a better solution:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad i = 1, 2, \dots, m. \quad (33)$$

4. Results

4.1. Simplified Numerical Model of PB-TES

To validate the simplified numerical model of PB-TES, a comparative analysis is performed between the simplified model and the one-dimensional transient heat transfer model [27] of a single-tank PB-TES under the simulation scenario. The results, presented in Figure 5, demonstrate that the load factor curves from both models are consistent, thereby confirming the accuracy and reliability of the simplified model.

4.2. Case Scenario

The NSHES is designed to meet the community load demand in Gansu Province, China. CSP plants for commercial operation are designed and operated in this area with abundant solar resources, and relevant scientific research of TMSR is conducted in Wuwei, Gansu. Wuwei is situated at 37.92° N latitude and 102.63° E longitude, with an elevation of 1570 m above sea level. The details of the weather data during a year obtained from

the NREL National Solar Radiation Database (NSRDB) [38] are presented in Table 1. It is essential to note that the weather database operates on U.S. time, so researchers must adjust the data to their local time for accurate application and analysis. The annual solar radiation in 2020 is illustrated in Figure 6. The operational parameters of the NSHES components are detailed in Table 2. Furthermore, the economic parameters for the NSHES components are provided in Table 3, while the parameters for the NSGA-II algorithm are detailed in Table 4.

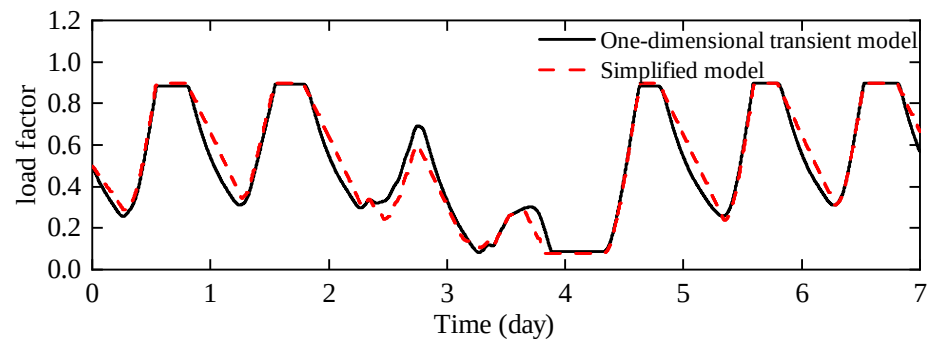


Figure 5. Comparative verification of the simplified model and the one-dimensional transient heat model.

The hourly average annual load is compiled using a German standard method according to the typical load curves provided by the China National Development and Reform Commission [39]. Then, the load data are scaled down by a factor of 55, and the modified curve is shown in Figure 7.

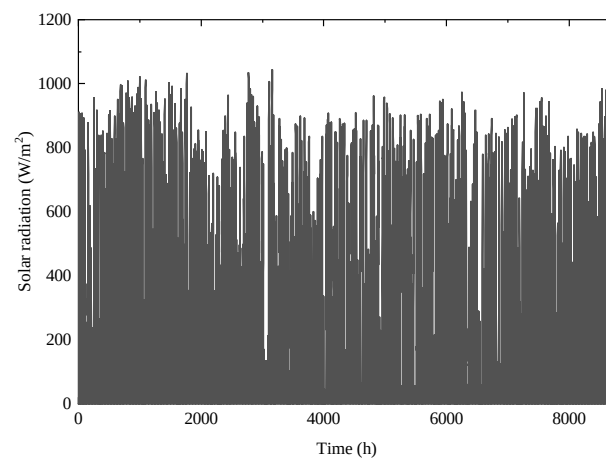


Figure 6. Hourly solar radiation for the study area.

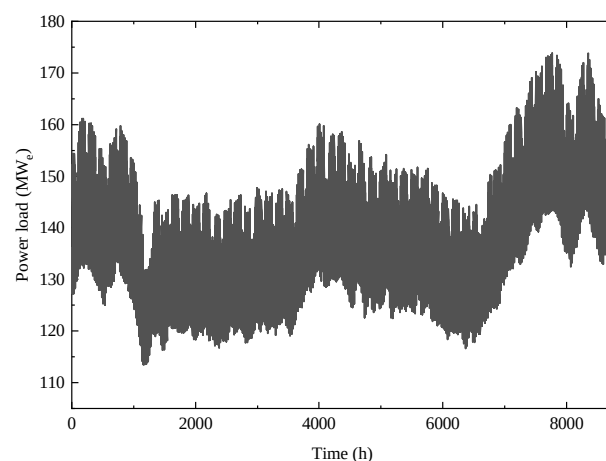


Figure 7. Hourly load demand for the designated study area.

Table 1. Annual meteorological data.

Parameter Name	Value
Annual sunshine hours (h)	3257.9
Annual DNI (W/m^2)	1044
Average temperature ($^{\circ}C$)	9.7
Maximum temperature ($^{\circ}C$)	38
Minimum temperature ($^{\circ}C$)	−35.1
Highest monthly average temperature ($^{\circ}C$)	21.7
Lowest monthly average temperature ($^{\circ}C$)	−9.8
Mean annual number of sandstorm days	8.2
Mean annual number of thunderstorm days	3.7
Annual precipitation (mm)	66.7
Average wind speed (m/s)	2.2
Maximum wind speed (m/s)	24

Table 2. Operational parameters of the NSHES system's components [25,27,31,40].

Component	Operation Parameter	Value
smTMSR CSP	Power (MW_e)	20
	Power (MW_e)	100
	Design DNI (W/m^2)	900
	Heliostat width (m)	5.662
	Heliostat height (m)	3.762
	Heliostat utilization rate (%)	94
	Tower height (m)	240
	Receiver diameter (m)	12
	Receiver height (m)	15
	Absorber panels number	32
	Heat pipes number of a single absorber panel	35
	Outer diameter of the absorber tube (mm)	33.4
	Wall thickness of the absorber tube (mm)	1.32
	Spacing between the absorber tubes (mm)	0.5
PB-TES	Receiver aperture area (m^2)	565.5
	Minimum temperature ($^{\circ}C$)	290
	Maximum temperature ($^{\circ}C$)	570
	Charging cut-off temperature ($^{\circ}C$)	320
	Discharging cut-off temperature ($^{\circ}C$)	540
	Maximum capacity (MWh_{th})	$0.90 \times C_{TES}^1$
	Minimum capacity (MWh_{th})	$0.05 \times C_{TES}$
PB	Initial capacity (MWh_{th})	$0.05 \times C_{TES}$
	Charging efficiency (%)	100
	Thermal efficiency (%)	40

¹ C_{TES} is the theoretical maximum storage capacity of the PB-TES.

Table 3. Economic parameters of the NSHES system's components [41–46].

Component	Economic Parameters	Value
smTMSR	Overnight capital cost ($\$/kW$)	3000
	Fixed O&M cost ($\$/kW$)	90.26
	Variable O&M cost ($\$/kWh$)	2.17
	Fuel cost ($\$/kWh$)	0.381
	Decommissioning cost ($\$/kW$)	621
	Operational lifespan (year)	20
CSP	Specific investment in solar fields ($\$/m^2$)	200
	Specific investment in land ($\$/m^2$)	1.25
	Specific investment in improvement ($\$/m^2$)	20
	Investment in receivers ($\$$)	$[66.46 \times (A_R/1440)^{0.7} \times 10^6]^1$
	Investment in towers ($\$$)	$[29.15 \times (H/203)^{0.1103} \times 10^6]^2$
PB-TES	O&M equipment cost percentage of investment per year (%)	1
	Operational lifespan (year)	20
	Initial investment cost ($\$/kWh_{th}$)	23.31
	O&M cost ($\$/kWh_{th}$)	0.1795
	Operational lifespan (year)	20
Heat exchanger	Initial investment cost ($\$/kW_{th}$)	45
	O&M cost ($\$/kW_{th}$)	0.9
	Operational lifespan (year)	20
PB	Initial investment cost ($\$/kW$)	298
	O&M cost ($\$/kW$)	5.96
	Operational lifespan (year)	20

¹ A_R is the equivalent diameter of the receiver. ² H is the height of the tower.

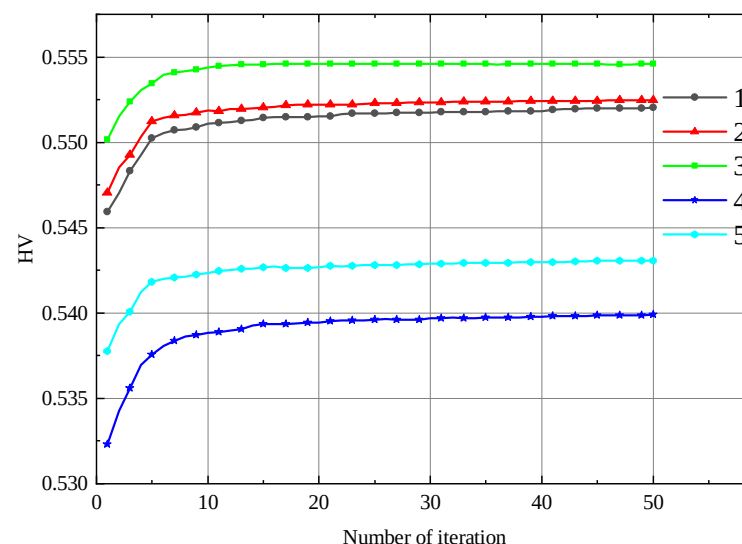
Table 4. Parameters of the NSGA-II algorithm.

Parameter	Value
Maximum iterations	50
Population size	300
Crossover probability	0.6
Simulated binary crossover distribution index	20
Expected number of mutated variables	1
Polynomial mutation distribution index	20

4.3. Optimal Configuration Analysis

NSGA-II is employed to optimize the NSHES under various operational modes, with a population of 300 and 50 iterations. The hypervolume (HV) indicator measures the volume formed between the set of all non-dominated solutions and a reference point in the objective space, which is a comprehensive index for evaluating the diversity and convergence of multi-objective algorithms. The algorithm runs five times separately with the same parameters based on PlatEMO [47], and the iteration processes of the HV are shown in Figure 8. The results demonstrate that the algorithm consistently achieves convergence across all five runs, indicating good stability.

Given the $20MW_e$ power output of a single smTMSR, the number of smTMSRs is excluded from the decision variables. To more effectively characterize the capacity allocation ratio between nuclear and CSP, the parameter $K_{nuc,sol}$ is defined as the ratio of smTMSR capacity to CSP capacity. It is noteworthy that the total installed capacity of the NSHES decreases significantly as the nuclear capacity reduces. Therefore, to ensure the rationality of simulation scenarios, the load curve is further proportionally scaled down as the nuclear installed capacity decreases. Pareto frontier curves for mode 1 at various values of $K_{nuc,sol}$ are presented in Figure 9. When the $K_{nuc,sol}$ is 0:100, the LCOE is highest under the condition of the same DPSP compared to other configurations. Furthermore, the configuration without smTMSR is unable to satisfy the DPSP requirement ($DPSP < 0.5\%$) [25]. As the $K_{nuc,sol}$ increases, the Pareto frontier curves tend to shift toward the lower-left region, which demonstrates an improvement in system reliability and the reduced cost of NSHES.

**Figure 8.** The HV convergence process of NSGA-II.

To compare the two operational modes, the Pareto frontier curves of the configuration with the $K_{nuc,sol}$ of 100:100 are presented in Figure 10. The difference between the two curves is minimal. The corresponding decision variables for different modes are illustrated in Figure 11. The SM curves and TSD curves in two modes are both nearly coincident.

Therefore, the impact of nuclear power adjustment on the optimization of the DPSP and LCOE is minimal.

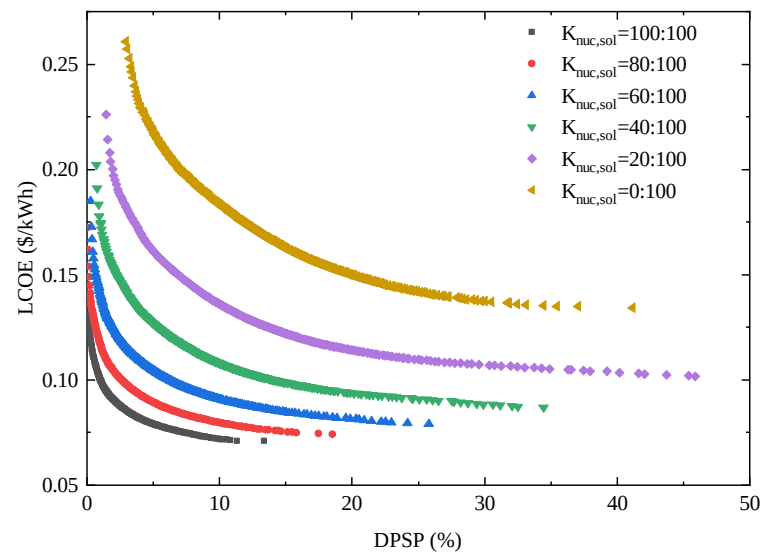


Figure 9. The Pareto frontier curves of mode 1 with different $K_{nuc,sol}$.

A collection of optimal solutions rather than a single option is produced through the multi-objective optimization process. Therefore, it is necessary to identify the best compromise solution. The objective weights are obtained through the CRITIC method, and the TOPSIS approach is then employed to evaluate and sort the Pareto solutions. The objective weights and corresponding values for the best compromise solutions of the two operation modes are detailed in Table 5. Taking $K_{nuc,sol}$ with 100:100 as an example, the optimal compromise solution for mode 1 yields a DPSP of 0.944% and an LCOE of 0.10142 \$/kWh, whereas for mode 2, the corresponding values are 0.920% and 0.10249 \$/kWh, respectively. The DPSP and LCOE of the best compromise solutions both increase significantly as $K_{nuc,sol}$ decreases in the two modes.

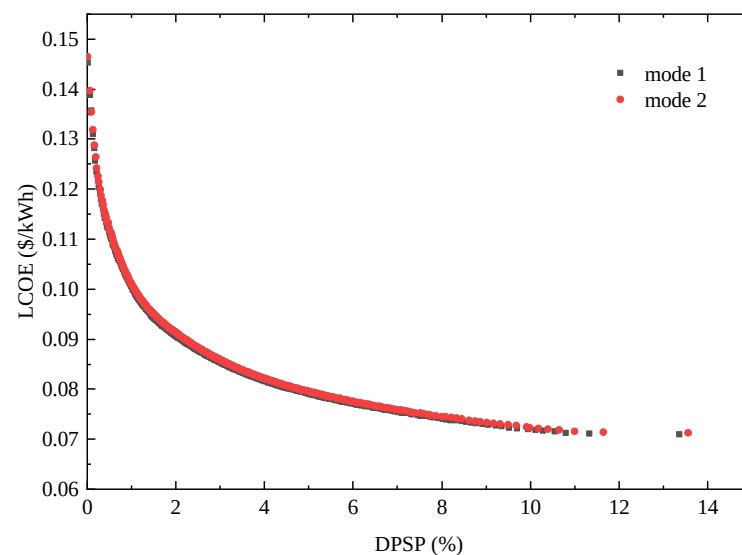


Figure 10. The Pareto frontier curves of the two operation modes with $K_{nuc,sol}$ of 100:100.

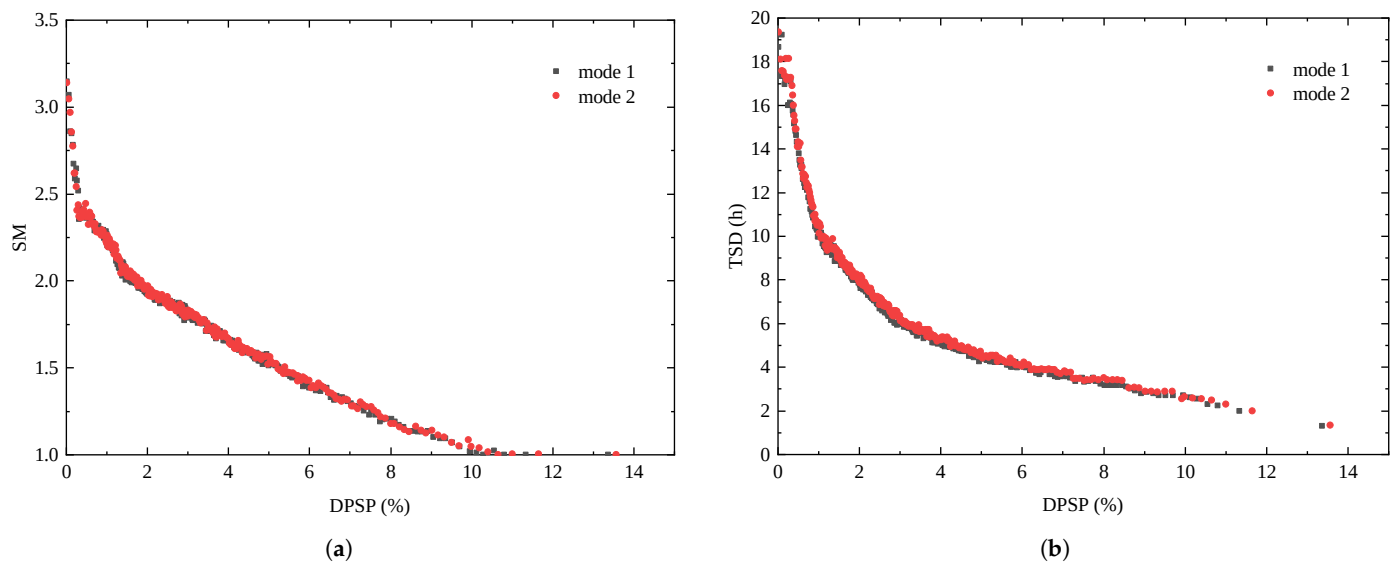


Figure 11. The corresponding decision variables, (a) SM and (b) TSD, of Pareto solutions in the two operation modes.

The optimal solutions with the requirement that the DPSP is less than 0.5% for various operation modes and $K_{\text{nuc,sol}}$ are summarized in Table 6. The electricity curtailment probability (ECP) is defined as the ratio of equivalent electricity of total curtailed heat to the total planned electricity generation. NSHSEs with $K_{\text{nuc,sol}}$ of 0:100, 20:100, and 40:100 fail to meet the system reliability requirements. As the nuclear installed capacity decreases, both the SM of CSP and TSD of TES increase to meet dispatch requirements, which results in a significant increase in overall system costs. The ECP increases obviously as $K_{\text{nuc,sol}}$ decreases because the fluctuated solar energy increases as SM increases. Furthermore, mode 2 exhibits a lower ECP compared to mode 1 with the same $K_{\text{nuc,sol}}$, which demonstrates that nuclear power adjustment could reduce energy curtailment.

Table 5. The best compromise solutions of the NSHES with different operating modes and different $K_{\text{nuc,sol}}$.

	$K_{\text{nuc/sol}}$	w_1	w_2	SM	TSD (h)	DPSP (%)	LCOE (\$/kWh)
mode 1	100:100	0.52452	0.47548	2.26971	10.33924	0.944	0.10142
	80:100	0.54038	0.45962	2.42768	13.22966	1.259	0.11270
	60:100	0.53872	0.46128	2.49466	15.74083	2.141	0.12278
	40:100	0.53375	0.46625	2.70384	23.17428	3.439	0.13718
	20:100	0.51430	0.48570	2.69812	23.44141	5.272	0.15921
	0:100	0.47344	0.52656	2.90859	31.81074	6.758	0.20154
mode 2	100:100	0.52230	0.47770	2.28622	10.66895	0.920	0.10249
	80:100	0.53770	0.46230	2.36516	13.39321	1.366	0.11174
	60:100	0.52658	0.47342	2.48992	15.84068	2.177	0.12292
	40:100	0.53415	0.46585	2.54521	19.63314	3.466	0.13746
	20:100	0.51640	0.48360	2.68874	23.66746	5.285	0.15934
	0:100	0.47344	0.52656	2.90859	31.81074	6.758	0.20154

Table 6. The best solutions of the NSHES with different operating modes and different $K_{\text{nuc,sol}}$ when DPSP is required to not be more than 0.5%.

	$K_{\text{nuc/sol}}$	SM	TSD (h)	DPSP (%)	LCOE (\$/kWh)	ECP, %
mode 1	100:100	2.36359	14.09935	0.493	0.1115	18.5
	80:100	2.64145	21.50056	0.486	0.13114	21.6
	60:100	3.00731	33.32513	0.471	0.16088	27.7
mode 2	100:100	2.37617	14.31337	0.499	0.11225	16.7
	80:100	2.57949	22.83108	0.475	0.13206	18.4
	60:100	3.02835	33.33333	0.480	0.16198	26.7

4.4. Power Contributions Analysis

Table 7 presents the power output proportions of the optimal solutions with the requirement that the DPSP is less than 0.5% for various operation modes and $K_{nuc,sol}$. As the $K_{nuc,sol}$ decreases, the proportion of smTMSR declines while the proportion of CSP and TES rise. Furthermore, compared to mode 1, the proportion of smTMSR in mode 2 reduces under the condition of the same $K_{nuc,sol}$.

Table 7. The contribution of the components to power output within the best solutions in different operation modes and $K_{nuc/sol}$ when DPSP is required to not be more than 0.5%.

	$K_{nuc/sol}$	Proportion of smTMSR, %	Proportion of CSP, %	Proportion of TES, %
mode 1	100:100	59.6	25.7	14.6
	80:100	53.6	27.1	19.3
	60:100	46.2	28.3	25.5
mode 2	100:100	58.3	25.9	15.8
	80:100	52.4	27.2	20.4
	60:100	45.0	28.5	26.5

4.5. Effect of Investment

In order to study the effect of NSHES component investment (investment in solar fields, land, towers, receivers, TES, power generation, and nuclear power) on the LCOE, the sensitivity analysis of investment is conducted by varying the investment in the reference case. The best compromise solutions of the NSHES with $K_{nuc,sol}$ of 100:100 in mode 2 is chosen as the reference case. The ratio of current investment to the baseline investment is defined as the investment ratio [37]. The LCOE ratio is obtained by dividing the current LCOE by the reference value. The sensitivity analysis of the investment costs for various components of the NSHES is shown in Figure 12. According to the results, the solar field investment contributes most significantly to variations in the LCOE, followed by the nuclear cost and the TES cost. A 25% reduction in the solar field cost leads to an approximate 7.2% decrease in the LCOE. By decreasing the cost of the solar field by 25%, the LCOE can be reduced by about 5.3%.

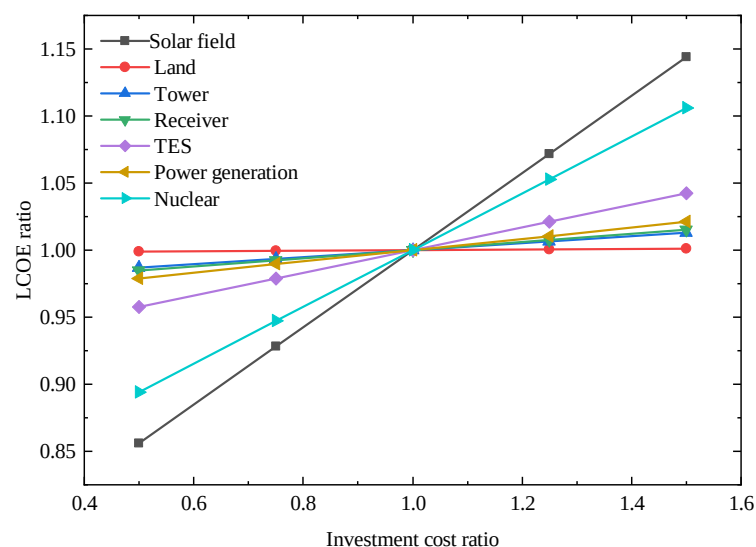


Figure 12. Sensitivity analysis of investment.

5. Conclusions

In this research, the NSHES, which consists of a smTMSR, CSP, and PB-TES with two operation modes, is proposed. The power of smTMSR is constant in mode 1 but dynamically

adjusted based on the LF of PB-TES in mode 2. In the NSHES configuration optimization problem, multi-objective optimization enables the generation of multiple Pareto solutions, and MCDM is then employed to choose the best compromise configuration from the solutions. This work aims to determine the optimal configuration of the NSHES to ensure demand–supply matching for the target community. The simplified numerical model of PB-TES is validated by comparing it with a one-dimensional transient heat transfer model, confirming the accuracy and reliability of the simplified approach.

The result of the Pareto frontier curves with different $K_{\text{nuc/sol}}$ shows that increasing the nuclear energy proportion can significantly enhance the stability and economic viability of NSHES. When the DPSP is required to remain below 0.5%, mode 2 results in a lower ECP than mode 1 with the same $K_{\text{nuc/sol}}$, which demonstrates that nuclear power adjustment could reduce energy curtailment. The ECP increases obviously as $K_{\text{nuc/sol}}$ decreases because the fluctuated solar energy increases as SM increases. The result of the power contribution analysis shows that the proportion of smTMSR in mode 2 reduces under the condition of the same $K_{\text{nuc/sol}}$ compared to mode 1. Finally, after adjusting the component investment based on the reference case, it is observed that the solar field investment contributes most significantly to variations in LCOE, followed by the nuclear cost and TES cost. The optimization approach for NSHES enhances the stability and economic feasibility of the system.

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Abbreviations

The following abbreviations are used in this manuscript:

O&M	operation and maintenance
smTMSR	small modular thorium molten salt reactor
CSP	concentrating solar power
TES	thermal energy storage
PV	photovoltaic
WT	wind turbine
MOPSO	multi-objective particle swarm optimization
NSGA-II	non-dominated sorting genetic algorithm
MCDM	multi-criteria decision-making
CRITIC	criteria importance through inter-criteria correlation
TOPSIS	technique for order preference by similarity to ideal solution
MADM	multi-attribute decision-making

MOEAs	multi-objective evolutionary algorithms
NSHES	nuclear–solar energy storage system
PB-TES	packed-bed thermal energy storage
PB	power block
LF	load factor
SAM	system advisor model
NREL	National Renewable Energy Laboratory
DNI	direct normal irradiance
SM	solar multiple
TSD	theoretical storage duration
LCOE	levelized cost of energy
DPSP	deficiency of power supply probability
NSRDB	NREL National Solar Radiation Database
HV	hypervolume
ECP	electricity curtailment probability

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