

Article

Stochastic Techno-Economic Optimization of Hybrid Energy System with Photovoltaic, Wind, and Hydrokinetic Resources Integrated with Electric and Thermal Storage Using Improved Fire Hawk Optimization

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Abstract: In this paper, a stochastic techno-economic optimization framework is proposed for three different hybrid energy systems that encompass photovoltaic (PV), wind turbine (WT), and hydrokinetic (HKT) energy sources, battery storage, combined heat and power generation, and thermal energy storage (Case I: PV–BA–CHP–TES, Case II: WT–BA–CHP–TES, and Case III: HKT–BA–CHP–TES), with the inclusion of electric and thermal storage using the 2m + 1 point estimate method (2m + 1 PEM) utilizing real data obtained from the city of Espoo, Finland. The objective function is defined as planning cost minimization. A new meta-heuristic optimization algorithm named improved fire hawk optimization (IFHO) based on the golden sine strategy is applied to find the optimal decision variables. The framework aims to determine the best configuration of the hybrid system, focusing on achieving the optimal size for resources and storage units to ensure efficient electricity and heat supply simultaneously with the lowest planning cost in different cases. Also, the impacts of the stochastic model incorporating the generation and load uncertainties using the 2m + 1 PEM are evaluated for different case results compared with the deterministic model without uncertainty. The results demonstrated that Case III obtained the best system configuration with the lowest planning cost in deterministic and stochastic models and. This case is capable of simply meeting the electrical and thermal load with the contribution of the energy resources, as well as the CHP and TESs. Also, the IFHO superiority is proved compared with the conventional FHO, and particle swarm optimization (PSO) achieves the lowest planning cost in all cases. Moreover, incorporating the stochastic optimization model, the planning costs of cases I–III are increased by 4.28%, 3.75%, and 3.57%, respectively, compared with the deterministic model. Therefore, the stochastic model is a reliable model due to its incorporating the existence of uncertainties in comparison with the deterministic model, which is based on uncertain data.

Keywords: hydrokinetic energy; stochastic optimization framework; electric and thermal energy storage; 2m + 1 point estimate method; golden sine strategy; improved fire hawk optimization



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1. Introduction

1.1. Motivation and Background

In remote regions lacking access to conventional power grids, the development of self-sustaining energy systems is essential to meet local energy demands [1]. These areas typically have diverse energy requirements encompassing both electrical and thermal needs, necessitating the integration of various energy sources and storage solutions into a unified

and dependable system [2]. Renewable sources, such as wind turbines (WTs), photovoltaic (PV) panels, and hydrokinetic (HKT) energy systems, are favored for their cost-effectiveness and minimal environmental impact [3]. Additionally, combined heat and power (CHP) systems are advantageous as they can produce heat and electricity simultaneously, making them ideal for regions with diverse energy consumption patterns [4]. By implementing these energy sources and CHP systems, reliable energy supply can be ensured in remote locations. However, a major challenge with these systems lies in the inherent variability in their daily power output, which may not always align perfectly with fluctuating daily energy demands. This mismatch underscores the need for effective storage solutions to balance supply and demand. Energy storage devices serve a key role by preserving extra power during periods of high production and releasing it when demand surges, thereby maintaining a consistent and reliable energy supply [5].

Developing a well-structured and sustainable hybrid energy system (HES) is a complex endeavor that demands careful, long-term planning spanning over a year. This phase identifies the optimal types and sizes of various energy resources and storage devices needed to meet energy demands [6]. A critical aspect of this planning is addressing uncertainties, particularly in predicting load and renewable energy source (RES) output. Accurate forecasts are essential for effective system planning, yet they are often challenged by inherent uncertainties [7]. These uncertainties stem from potential differences between actual energy demand and RES generation compared to their anticipated values in deterministic models. Consequently, this unpredictability may require incorporating more storage devices than initially estimated to ensure system reliability and efficiency [7]. To enhance the efficiency of energy systems in off-grid applications, understanding these uncertainties comprehensively is essential. A resilient energy system must adapt to the dynamic and sometimes unpredictable nature of renewable energy sources, necessitating investments in advanced storage technologies and sophisticated predictive models that anticipate fluctuations in energy production and consumption [8]. Furthermore, continuous monitoring and adaptive management are vital to respond to real-time data and evolving conditions, ensuring sustained efficiency and reliability [8]. Successfully deploying these systems in remote areas also depends significantly on socio-economic factors. Therefore, creating self-sustaining energy systems in remote regions is a multifaceted challenge that requires an integrated approach. By integrating diverse energy sources, implementing advanced storage solutions, and meticulously addressing uncertainties through strategic planning, it becomes feasible to develop dependable energy systems tailored to the unique requirements of off-grid applications [9].

1.2. Related Works and Gaps

Several studies have addressed the topic of optimizing off-grid energy systems that include various energy sources and storage. Some of these studies discuss the use of energy sources, storage devices, load types, optimization approaches, and probabilistic methodologies. A method is described for sizing two PV–battery and PV–wind–battery systems, and thus the energy generation cost is minimized utilizing an ascending algorithm-based iterative strategy based on an energy management approach with the goal of lowering the net present and energy costs in [10]. The sizing of a PV–battery system is presented in [11] aimed at reducing costs while accounting for data changes, as well as energy management to meet demand with high reliability. The ideal size of renewable resources and storage is discovered in off-grid and on-grid operation phases in [12], and reliability indexes have also been developed to obtain the most dependable and cost-effective system. Weather parameters, load profiles, and design data are employed in [13] to optimize a hybrid PV–hydrogen system for generating renewable power and meeting consumption in particular Indian locations. An off-grid energy system optimization via WT, PV, diesel generator, battery, and EVs is carried out in [14] to reduce the investment, maintenance, and operation costs of assets and storage while also reducing emissions, and different uncertain parameters have been included to determine the system’s optimal configuration.

An elephant herd optimization technique is employed to optimize a system in [15] that utilizes energy units, fuel, and storage-based battery supply, decreasing load loss, emissions, and running costs. An optimization framework is performed for an HES, including WTs, and multi-carrier energy storage considering demand response (DR) to minimize the operating cost using a gray wolf algorithm incorporating the uncertainties of load and generation [16]. An optimization framework for planning incorporating renewable resources and a gas–electric grid is proposed in [17]. An artificial network is utilized for a self-adaptable energy management system of an HES to improve microgrid performance via PSO, which optimizes every neural network to determine and deliver input to the management of energy, in [18]. Microgrid energy management is developed, incorporating electric the market price methodologies, while taking into account grid participation requirements and the involvement of the DR in [19]. An energy optimization technique for microgrid system planning is established in [20], taking into account electrical, heating, and refrigeration to improve microgrid dependability based on multi-layer energy planning to reduce operational and emission costs. An effective energy management system for a microgrid is constructed utilizing a new algorithm with cost and pollution reductions employing a manta ray foraging optimization with uncertainties and PEM in [21]. An energy management technique to managing uncertainty in microgrids is illustrated by using energy storage devices to minimize a microgrid’s anticipated cost, taking into account two WT and solar energy generation uncertainties, in [22]. An economic dispatch for an independent microgrid is provided in [23] with the goal of minimizing cost while taking into account the capacity of the energy storage systems. An MILP strategy for minimizing the operating expenses of an off-grid energy system is proposed and validated using the rotational reserve’s probability limitations in [24]. Rotating reserve constraints are examined in [25], taking into account battery energy storage power availability for handling contingencies in an off-grid hybrid system made up of energy units because of the uncertainties of energy production from renewable sources. An optimization structure has been offered for incorporating an incentive-based DR and reconfiguration in the microgrid considering renewable uncertainties via the PEM to reduce fuel and DG costs while maximizing earnings for the microgrid operator [26]. A two-stage stochastic energy management system is utilized for a microgrid with CHP and distribution compensator and energy storage using the $2m + 1$ PEM in [27]. The best placement of battery storage and energy resources in the distribution network is constructed while accounting for a loss sensitivity factor, and PEM is used to model the uncertainty in [28]. This approach tries to discover the appropriate size and timing of battery energy storage by minimizing fluctuations in voltage and losses in the network. A stochastic method is created for the best performance of a PV–WT–fuel cell–MT–battery system to reduce system cost while taking smart homes’ involvement in DR into account, utilizing a randomization technique [29]. To mitigate the consequences of uncertainty, several strategies have been used for HES optimization. Those techniques comprise Monte Carlo simulation (MCS), analytical, and approximation methods [7–9,21,22,27]. MCS is one of the best-known and preferred methods. The second category includes analytical approaches, which use simplifications to predict uncertainty effects at a lower computing cost than MCS. The PEM is the most prominent technique in the third category.

Based on the literature review on optimizing HESs, several research gaps are presented, as follows.

- Current studies primarily focus on optimizing energy resources and storage solutions for electrical energy supply, often neglecting thermal load considerations [10–16,18–26,28,29]. Recently, attention has turned to integrating combined heat and power (CHP) systems to enhance power generation efficiency. The incorporation of thermal storage with CHP systems is anticipated to significantly enhance system performance, reduce operational costs, and lower emissions. However, research on this integrated approach remains relatively scarce in HES planning.

- The integration of hydrokinetic energy into HESs, particularly in conjunction with CHP and battery energy storage for electrical load supply, is another underexplored area in the literature [10–29]. Combining hydrokinetic energy with CHP and battery storage can notably improve the efficiency of these systems. Hydrokinetic energy offers a reliable renewable electricity source that, when paired with CHP and batteries, ensures a stable and cost-effective energy supply.
- There is a notable gap in addressing uncertainties in HES optimization and planning. Optimizing these systems without accounting for uncertainties in resource generation and load demand leads to unreliable outcomes. This oversight is evident in [10–13,17–20,23,24]. While Monte Carlo simulation (MCS) has been applied to tackle uncertainties, the point estimate method (PEM) offers advantages such as computational efficiency, faster analysis, simplicity, accuracy, intuitive understanding, and scalability. PEM proves beneficial for optimizing HESs, especially in scenarios where computational resources are limited and rapid, dependable results are crucial.
- The literature also highlights that while various meta-heuristic optimization algorithms are used in HES planning, no single algorithm universally solves all problems, as per the “no free lunch” theory. Enhancing these algorithms with advanced mathematical techniques can improve their exploration capabilities, preventing them from converging on local optima and thereby yielding more efficient solutions. However, this area has received relatively less attention in previous research.

1.3. Contributions

Based on the literature review, the significant advancements in optimizing and planning HESs involving various energy resources and storage can be summarized as follows.

- This study investigates the optimization and planning of three HES configurations including PV, WT, hydrokinetic (HKT) resources, CHP, and thermal energy storage (TES). Case I uses hybrid PV–BA–CHP–TES, Case II hybrid WT–BA–CHP–TES, and Case III hybrid HKT–BA–CHP–TES. These configurations utilize CHP, electric, and thermal storage to simultaneously supply electrical and thermal loads while minimizing planning costs.
- A new optimizer, named improved fire hawk optimization (IFHO) and employing a golden sine strategy, is utilized in this research. The IFHO aims to achieve optimal solutions with minimal standard deviation in response and high convergence speed.
- The research employs the $2m + 1$ point estimate method (PEM) for uncertainty modeling in renewable generation and electric and thermal loads. PEM offers computational efficiency, quick analysis, simplicity, accuracy, intuitive interpretation, and scalability. Hence, PEM proves advantageous for optimizing HESs, especially in scenarios with limited computational resources, providing rapid and reliable results compared to Monte Carlo simulation, which involves high computational costs.

1.4. Paper Structure

The rest of the paper is presented as follows. The proposed methodology, including HS modeling, objective function, constraints, the proposed optimizer and its implementation, and $2m + 1$ PEM for stochastic modeling, is presented in Section 2. The simulation results and discussion of several cases are given in Section 3. Finally, the outcomes of the paper are summarized in Section 4.

2. Methodology

In this section, the proposed methodology is presented for stochastic optimization of different configurations of an HES to supply electrical and thermal demand considering generation and load uncertainties using the $2m + 1$ PEM and IFHO to minimize the planning cost.

2.1. HS Model and Operation

This study investigates three off-grid HESs, as illustrated in Figure 1, integrating PV, WT, HKT, and CHP sources, alongside electric battery storage and TESs. The configurations are Case I: PV–battery–CHP–TES, Case II: WT–battery–CHP–TES, and Case III: HKT–battery–CHP–TES. The CHP system, in conjunction with TES, provides the required thermal load, while PV, WT, HKT, and CHP sources collectively cater to the electrical load. In instances where these sources are insufficient to meet the load demands, the battery storage system steps in to supply electrical power.

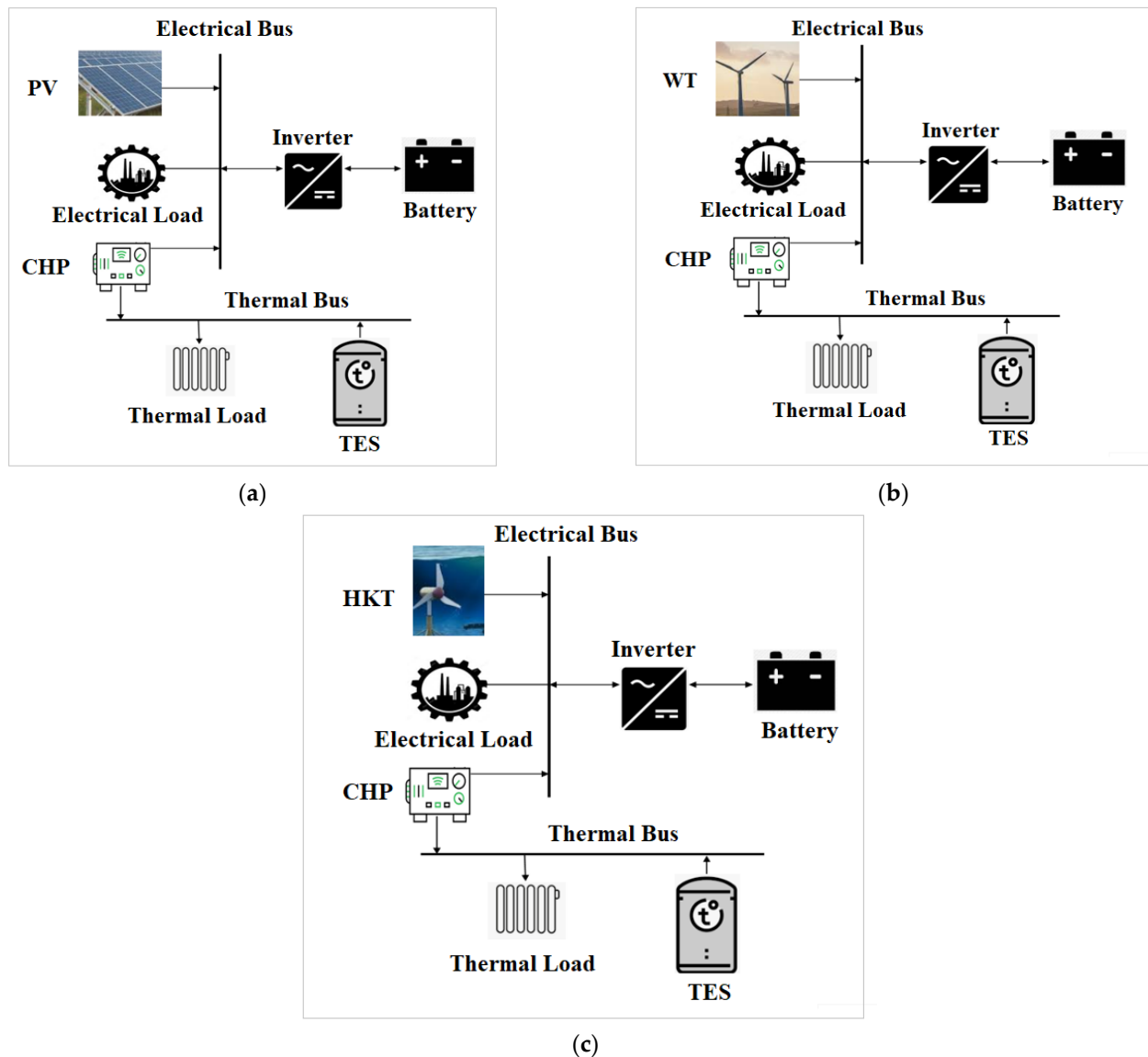


Figure 1. The schematic of the HESs under study: (a) PV–battery–CHP–TES; (b) WT–battery–CHP–TES; (c) HKT–battery–CHP–TES.

Operationally, the system functions as follows:

- Excess electricity generated by renewable sources and CHP is directed to charge the batteries.
- When renewable sources and CHP cannot meet the electrical load demands, batteries discharge stored power to compensate.
- For thermal load provision, surplus thermal power generated by CHP is stored in TES.

- Conversely, when CHP-produced thermal power falls short of demand, TES supplements the shortfall.

This operational framework ensures efficient utilization of energy production sources and storage devices to maintain reliable operation under varying load conditions.

2.2. Objective Function

The proposed methodology defines the objective function as minimizing the planning cost [30–32], which includes annual installation, maintenance, and operation costs, as well as emission costs, by:

$$\text{Total Cost} = C_I^{HS} + C_M^{HS} + C_O^{HS} + C_{Ems}^{HS} \quad (1)$$

$$C_I^{HS} = (C_{I-PV.WT.HKT} N_{PV.WT.HKT} + C_{I-B} N_B + C_{I-I} N_I + C_{I-TES} N_{TES} + C_{I-CHP} P_{CHP}^{max}) \times CRF \quad (2)$$

$$C_M^{HS} = C_{M-PV.WT.HKT} N_{PV.WT.HKT} + C_{M-B} N_B + C_{M-I} N_I + C_{M-TES} N_{TES} + C_{M-CHP} P_{CHP}^{max} \quad (3)$$

$$C_O^{HS} = C_{O-CHP} \quad (4)$$

$$C_{Ems}^{HS} = C_{E-CHP} \quad (5)$$

$$CRF = \frac{ir(1+ir)^G}{(1+ir)^G - 1} \quad (6)$$

where $N_{PV.WT.HKT}$ is the number of PVs, WTs, and HKTs, N_B is the number of batteries, N_I denotes inverter number, N_{TES} refers to the quantity of thermal energy storage, and $C_{I-PV.WT.HKT}$, C_{I-B} , C_{I-TES} , and C_{I-CHP} denote yearly installation cost of renewable units, battery, TES, and CHP capacity (USD/year). $C_{M-PV.WT.HKT}$, C_{M-B} , C_{M-I} , C_{M-TES} , and C_{M-CHP} are maintenance costs of renewable units, battery, TES, and CHP capacity (USD/kW/year), C_{O-CHP} is yearly operating cost (USD/year), and C_{E-CHP} refers to the emission cost (USD/year) of the HES. CRF denotes the factor of capacity recovery. Also, ir and G are the interest rate, and component lifespan, respectively.

2.3. HS Components Model

2.3.1. PV

The unpredictable nature of solar irradiance (s_h) during the time interval “h” and within scenario “w” is modeled using a beta probability distribution function (PDF). This method is mathematically represented in [33]. The beta distribution is particularly suitable for this purpose because it can effectively capture the variability and randomness of solar irradiance. Based on parameterizing the distribution with shape parameters, the beta PDF can be tailored to reflect different irradiance conditions observed in real-world scenarios, such as clear or cloudy days. This probabilistic modeling is crucial for accurately assessing the performance and reliability of solar energy systems under various weather conditions, enabling more robust and efficient system design and planning.

The beta PDF for uncertain irradiance behavior is defined by [33]:

$$f_{ird,h,w} = \frac{\Gamma(k_{s,h,w} + c_{s,h,w})}{\Gamma(k_{s,h,w}) + \Gamma(c_{s,h,w})} (s_{h,w})^{k_{s,h,w}-1} (1 - s_{h,w})^{c_{s,h,w}-1} \text{ for } k_{s,h,w} > 0; c_{s,h,w} > 0 \quad (7)$$

where Γ represents the gamma function, while k_s and c_s denote the shape parameters at time interval “h.” These parameters are calculated using the mean ($\mu_{ird,h,w}$) and standard deviation ($\sigma_{ird,h,w}$) of the irradiance in the corresponding time interval.

$$c_{s,h,w} = (1 - \mu_{ird,h,w}) \left(\frac{\mu_{ird,h,w}(1 + \mu_{ird,h,w})}{(\sigma_{ird,h,w})^2} - 1 \right) \quad (8)$$

$$k_{s,h,w} = \frac{\mu_{ird,h,w} c_{s,h,w}}{(1 - \mu_{ird,h,w})} \quad (9)$$

At every time interval, the $2m + 1$ PEM [33] is applied to account for the uncertainty in solar irradiance by assessing its concentration. The PV power output depends on the received irradiation and temperature of ambient air. The power produced by PV arrays is calculated as follows [2,7,13]:

$$P_{PV,h,w} = P_{PVrated} \times N_{PV} \times \frac{ird_{h,w}}{ird_{ref}} \times [1 + \mu_T(T_{c,h,w} - T_{STC})] \quad (10)$$

$$T_{c,h,w} = T_{ambient,h,w} + \left[\frac{NOCT - 20}{800} \right] \times ird_{h,w} \quad (11)$$

where $P_{PVrated}$ is the nominal power of the PV system, while $ird_{h,w}$ and ird_{ref} denote the irradiance at time h and the standard test condition (STC) irradiance, respectively. μ_T signifies the PV temperature coefficient ($(-3.7 \times 10^{-3} (1/^\circ\text{C}))$). $T_{c,h,w}$, T_{STC} , and $T_{ambient,h,w}$ represent the cell temperature at time h and scenario w , the standard test condition temperature, and the ambient temperature at time h , respectively. $N_{PV} \in \{1, 2, \dots, N_{PV,max}\}$ denotes the total number of PV units, $N_{PV,max}$ referring to the maximum allowable number of PVs in the HES. $NOCT$ indicates the nominal operating cell temperature ($^\circ\text{C}$).

2.3.2. WT

The probabilistic characteristics of wind speed (v_h) during a specified time period are presented using the Weibull PDF, expressed in [33]:

$$f_{wind,h,w} = \frac{k_{wind,h,w}}{c_{wind,h,w}} \left(\frac{v_{h,w}}{c_{wind,h,w}} \right)^{k_{wind,h,w}-1} e^{-\left(\frac{v_{h,w}}{c_{wind,h,w}} \right)^{k_{wind,h,w}}} \quad (12)$$

The parameters of shape ($k_{wind,h}$ and $c_{wind,h}$) at time h are related to $\mu_{wind,h,w}$ and $\sigma_{wind,h,w}$ at the corresponding time and are computed as follows:

$$k_{wind,h,w} = \left(\frac{\sigma_{wind,h,w}}{\mu_{wind,h,w}} \right)^{-1.086} \quad (13)$$

$$c_{wind,h,w} = \frac{\mu_{wind,h,w}}{\Gamma(1 + 1/k_{wind,h,w})} \quad (14)$$

The total WT power during time h for scenario ω depends on different wind speed categories, as defined by [17,30,34]:

$$P_{WT,h,w} = \begin{cases} P_{WTrated} \times N_{WT} \times \left(\frac{v_{h,w} - v_{ci}}{v_{rated} - v_{ci}} \right); & v_{ci} \leq v_{h,w} \leq v_{rated} \\ P_{WTrated} \times N_{WT} & ; v_{rated} \leq v_{h,w} \leq v_{co} \\ 0 & \text{Otherwise} \end{cases} \quad (15)$$

where $P_{WTrated}$ is the rated WT unit power, and v_{ci} , v_{co} , and v_{rated} are the cut-in, cut-out, and nominal wind speed, respectively. $N_{WT} \in \{1, 2, \dots, N_{WT,max}\}$ is the total WT unit numbers, and $N_{WT,max}$ denotes the maximum number of WTs.

2.3.3. HKT

The variable water flow speed uncertainty (wf_h) over time interval “ h ” in the hydrokinetic (HKT) model is hypothesized to conform to the Weibull PDF by:

$$f_{hkt,h,w} = \frac{k_{hkt,h,w}}{c_{hkt,h,w}} \left(\frac{wf_{h,w}}{c_{hkt,h,w}} \right)^{k_{hkt,h,w}-1} e^{-\left(\frac{wf_{h,w}}{c_{hkt,h,w}} \right)^{k_{hkt,h,w}}} \quad (16)$$

The parameters of shape $k_{hkt.h.w}$ and $c_{hkt.h.w}$ at time h and in scenario w are related to $\mu_{hkt.h.w}$ and $\sigma_{hkt.h.w}$ at a similar time and are defined as follows:

$$k_{hkt.h.w} = \left(\frac{\sigma_{hkt.h.w}}{\mu_{hkt.h.w}} \right)^{-1.086} \quad (17)$$

$$c_{hkt.h.w} = \frac{\mu_{hkt.h.w}}{\Gamma(1 + 1/k_{hkt.h.w})} \quad (18)$$

The HKT performance resembles that of traditional hydropower plants, fostering their increased adoption and advancement. Tidal currents are harnessed to generate power using horizontal axis turbines in this research. The power produced by HKT, factoring in cut-in, cut-out, and rated water flow, is computed as detailed in [34]:

$$P_{HKT.h.w} = \begin{cases} 0 & ; w f_{h.w} \leq w f_{ci}, w f_{h.w} \geq w f_{co} \\ N_{HKT} \times 0.5 \delta A C_P w f_{h.w}^3 & ; w f_{ci} < w f_{h.w} < w f_{rated} \\ P_{HKT.rated} \times N_{HKT} & w f_{rated} \leq w f_{h.w} \leq w f_{co} \end{cases} \quad (19)$$

where $P_{HKT.h.w}$ and $P_{HKT.rated}$ refer to the HKT power at time h and rated HKT power (kW), respectively, $w f_{h.w}$ denotes the water flow speed at time h , $w f_{ci}$ refers to the cut-in water flow speed, $w f_{rated}$ denotes the nominal water speed, and $w f_{co}$ refers to the cut-out water speed (m/s). δ is fluid density (kg/m³), A denotes turbine cross-sectional area (m²), and C_P is coefficient of power. $N_{HKT} \in \{1, 2, \dots, N_{HKT.max}\}$ is the HKT unit numbers, and $N_{HKT.max}$ is the maximum number of HKTs.

2.3.4. CHP

In this study, priority is given to CHP in meeting the heat load demand [17]. Nevertheless, to minimize operational costs and emission impact, TES [35,36] is combined with CHP. So, the decision variable for CHP power (P_C) at time h and scenario ω is considered based on the problem objectives and constraints. The allowable variation limit of the change in CHP power ($P_{chp.h.w}$) is calculated as:

$$P_{chp.h.w} \in [0 \quad P_{CHP.max}] \quad (20)$$

where $P_{CHP.max}$ denotes the greatest value of the CHP power.

The CHP thermal power ($H_{CHP.h.w}$) is calculated by [17]:

$$H_{CHP.h.w} = \frac{(1 - \eta_T - \eta_L)\eta_H}{\eta_T} \times P_{CHP.h.w} \quad (21)$$

where η_T , η_L , and η_H refer to the turbine, losses, and heating part efficiencies, respectively.

The allowable variations in H_C are presented by:

$$H_{CHP.h.w} \in \left[0 \quad \frac{(1 - \eta_T - \eta_L)\eta_H}{\eta_T} \times P_{CHP.max} \right] \quad (22)$$

The CHP annual cost is computed as follows:

$$FC_{CHP} = 365 \times CF \times \sum_{h=1}^{24} \sum_{\omega=1}^{n_{\omega}} \pi(\omega) \times f p_c \times (\chi_C P_C^{max} + \gamma_C P_{CHP.h.w}) \quad (23)$$

where $f p_c$ denotes the CHP fuel consumption cost. χ_C and γ_C refer to the coefficients related to the consumption of CHP fuel. π denotes the probability of scenario occurrence, and n_{ω} denotes the scenarios number. CF is the factor of coincidence.

The cost of yearly emissions for CHP is calculated by:

$$EC_{CHP} = 365 \times CF \times \sum_{h=1}^{24} \sum_{\omega=1}^{n_{\omega}} \pi(\omega) \times ep_C \times \beta_C P_{CHP,h,w} \quad (24)$$

where ep_C refers to the emission penalty price. β_C represents the total coefficients of NO_x , CO_2 , and SO_2 emissions [17,37].

2.3.5. TES

If the thermal CHP generated during time τ and for scenario ω exceeds the thermal demand (H_L), then TESs will function in charge mode. The saved TES energy (E_T) at time h for scenario ω can be determined as per [35,36]:

$$E_{TES,h,w} = (1 - \partial) \times E_{TES,h-1,w} + \eta_T^c \times (H_{CHP,h,w} - H_{LD,h,w}) \quad \forall H_{CHP,h,w} > H_{LD,h,w} \quad (25)$$

where η_T^c is the charging efficiency of TES and ∂ denotes hourly discharge rate.

When the CHP does not produce enough heat to meet the heat load, the TESs release their stored energy. In these conditions, the calculation for the saved energy in TES at time h is defined by:

$$E_{TES,h,w} = (1 - \partial) \times E_{TES,h-1,w} - \frac{1}{\eta_T^d} \times (H_{LD,h,w} - H_{CHP,h,w}) \quad \forall H_{CHP,h,w} < H_{LD,h,w} \quad (26)$$

where η_T^d is the efficiency of discharging the TES.

The saved energy size constraint in TESs is considered as follows:

$$E_{TES,h,w} \in [N_{TES} E_{TES,min} \quad N_{TES} E_{TES,max}] \quad (27)$$

where $N_{TES} E_{TES,min}$ and $N_{TES} E_{TES,max}$ refer to the lowest and highest energy storage sizes in the TES, respectively. N_{TES} is the TES numbers that can be installed in the HES and is presented as follows:

$$N_{TES} \in \{1, 2, \dots, N_{TES,max}\} \quad (28)$$

where $N_{TES,max}$ denotes the maximum number of TESs.

2.3.6. Battery

When the combined power of CHP and WTs exceeds the electrical demand (P_L) during time τ and scenario ω , the surplus active power is stored in batteries [15,24,28]. Therefore, the calculation for the energy stored in the battery (E_B) at time h is as follows:

$$E_{B,h,w} = (1 - \partial) \times E_{B,h-1,w} + \eta_B^c \times \eta_I (P_{PV,h,w} + P_{WT,h,w} + P_{HKT,h,w} + P_{CHP,h,w} - P_{LD,h,w}) \quad \forall P_{PV,h,w} + P_{WT,h,w} + P_{HKT,h,w} + P_{CHP,h,w} > P_{LD,h,w} \quad (29)$$

When the total output of CHP and wind units falls short of the electrical load, batteries supply the additional active power required. Therefore, E_B is computed by:

$$E_{B,h,w} = (1 - \partial) \times E_{B,h-1,w} - \frac{1}{\eta_B^d \times \eta_I} (P_{LD,h,w} - (P_{PV,h,w} + P_{WT,h,w} + P_{HKT,h,w} + P_{CHP,h,w})) \quad \forall P_{PV,h,w} + P_{WT,h,w} + P_{HKT,h,w} + P_{CHP,h,w} < P_{LD,h,w} \quad (30)$$

The parameters η_B^c and η_B^d represent the efficiency of battery charging and discharging, respectively, while η_I denotes the inverter efficiency. The limit for the amount of energy that can be stored in the battery bank is specified by:

$$E_{B,h,w} \in [N_B E_{B,min} \quad N_B E_{B,max}] \quad (31)$$

where $E_{B,min}$ and $E_{B,max}$ denote the battery's lower and upper bounds of stored energy, respectively.

The number of batteries in the HES (N_B) is defined in relation to the constraint:

$$N_B \in \{1, 2, \dots, N_{B,max}\} \quad (32)$$

where $N_{B,max}$ denotes the maximum number of batteries.

2.3.7. Inverter

In the HES being studied, the inverter enables the integration of batteries into the AC bus. Given that the maximum demand flowing by the inverter is denoted as $P_{I,max}$ [17], the system required for inverters to support the highest load flow of the batteries is computed as follows:

$$n_I = \left\lceil \frac{\max(P_B)}{P_{I,max}} \right\rceil + 1 \quad \forall P_{B,h,w} = E_{B,h,w} - E_{B,h-1,w} \quad (33)$$

where P_B denotes the active power of batteries.

2.3.8. Load

The electrical and thermal load requirements of the HES are variables that are uncertain and require investigation during system planning. The most suitable PDF for describing these loads is the normal distribution function [38], which is expressed as:

$$f_{ld,h,w} = \frac{1}{\sigma_{ld,h,w} \sqrt{2\pi}} e^{-\frac{(ld,h,w - \mu_{ld,h,w})^2}{2\sigma_{ld,h,w}^2}} \quad (34)$$

where ld,h,w is the load at time h , $f_{ld,h,w}$ denotes the normal PDF, and $\mu_{ld,h,w}$ and $\sigma_{ld,h,w}$ are the load mean and the deviation, respectively.

2.4. Proposed Optimizer

This study utilizes an improved fire hawk optimization (IFHO) to optimize the HES and determine the decision variables. This section presents the formulation of IFHO and its application in addressing the problem.

2.4.1. Fire Hawk Optimizer (FHO)

This study focuses on optimizing the HES within distribution networks using an IFHO, which draws inspiration from Aboriginal Australian fire management practices and the predatory strategies of fire hawks. Similar to how these birds use fire to drive prey into the open, IFHO employs a problem-solving approach that mimics this behavior. The research integrates cultural and natural phenomena into a mathematical model to enhance the efficiency of the system, showcasing a novel meta-heuristic optimization technique derived from observations of ecological balance and hunting tactics in the wild. The IFHO mirrors the processes of initiating and spreading fires, analogous to the behavior of fire hawks hunting for prey. Initially, location vectors representing the hawks and prey are identified, generating multiple potential solutions (X). These vectors' initial coordinates within the search space are determined via a starting technique randomly [39]:

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} x_{1,1} & X_{1,2} & \cdots & \cdots & x_{1,j} & x_{1,d-1} & x_{1,d} \\ x_{2,1} & X_{2,2} & \cdots & \cdots & x_{2,j} & \cdots & x_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{N,1} & X_{N,2} & \cdots & \cdots & x_{N,j} & x_{N,d-1} & x_{N,d} \end{bmatrix}, \quad \begin{cases} i = 1, 2, \dots, N \\ j = 1, 2, \dots, d \end{cases} \quad (35)$$

$$x_i^j(0) = x_{i,min}^j + rand. \cdot (x_{i,max}^j - x_{i,min}^j), \quad \begin{cases} i = 1, 2, \dots, N \\ j = 1, 2, \dots, d \end{cases} \quad (36)$$

where X_i denotes the i th potential answer within the search space; d is the problem's dimensionality; N is the potential solutions number in the search space; x_i^j signifies the j th variable of the i th potential solution; $x_i^j(0)$ indicates the primary location of the first two potential answers; $x_{i,min}^j$ and $x_{i,max}^j$ represent the lower and upper bounds of the j th variable of the i th potential solution, respectively; and $rand$ denotes a randomly generated number uniformly distributed within the range $[0, 1]$.

The optimization problem addressed by the objective function (OF) investigation involves positioning hawks within the search space. While other candidates represent potential prey, those with the highest objective function (OF) values are identified as fire hawks. These designated fire hawks spread fires throughout the search area, aiding in hunting. Additionally, the primary fire ignited by the fire hawks across the search area is considered the optimal global solution. These behavioral characteristics are described as follows [39]:

$$PR = \begin{bmatrix} PR_1 \\ PR_2 \\ \vdots \\ PR_l \\ \vdots \\ PR_n \end{bmatrix}, k = 1, 2, \dots, m \quad (37)$$

$$FH = \begin{bmatrix} FH_1 \\ FH_2 \\ \vdots \\ FH_l \\ \vdots \\ FH_n \end{bmatrix}, l = 1, 2, \dots, n \quad (38)$$

where FH_l refers to the l th fire hawk among a total of n hawks within the search space, and PR_k represents the k th prey among m preys within the search space. The optimizer then proceeds to compute the total distance between the fire hawks and the prey in the following step. An illustration of this concept is given in Figure 2, where D_k^l is computed using the formula provided [39]:

$$D_k^l = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}, \begin{cases} l = 1, 2, \dots, n \\ k = 1, 2, \dots, m \end{cases} \quad (39)$$

where m and n denote the total prey and fire hawks numbers in the search area, respectively, and (x_1, y_1) and (x_2, y_2) indicate the positions of the prey and fire hawks within the search area. Additionally, D_k^l represents the total distance between the l th fire hawk and the k th prey.

In the next step of the optimizer, fire hawks collect burning twigs from the fire to start fires in specific locations. During this process, prey swiftly evacuate as each bird grabs a burning stick and places it in the designated area. The following formula illustrates how these actions function as location-update methods during the primary search cycle of FHO, where some birds actively use burning sticks gathered from other fire hawks' territories in the meantime [39].

$$D_k^l = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}, \begin{cases} l = 1, 2, \dots, n \\ k = 1, 2, \dots, m \end{cases} \quad (40)$$

In this stage, r_1 and r_2 denote distributed probabilities uniformly ranging from $(0, 1)$, utilized to find the movements of fire hawks towards the primary fire and the boundaries, respectively. GB represents the optimal solution identified as the main fire within the search area. FH_{Near} denotes one of several fire hawks in the search space, and the updated

location vector of the l th fire hawk (FH_l) is denoted as F_{new}^l . The prey movement around each fire hawk is crucially incorporated in the subsequent step of the method, updating their positions. When a fire hawk places a burning stick, its prey may flee, hide, or unintentionally move towards the fire hawk. Accounting for these movements during position updates can be accomplished using the equation provided in [39]:

$$PR_q^{new} = PR_q + (r_3 \times FH_l - r_4 \times SP_l), \begin{cases} l = 1, 2, \dots, n \\ q = 1, 2, \dots, r \end{cases} \quad (41)$$

where GB represents the globally optimal solution within the space of search, identified as the initial fire; SP_l indicates the secure position under the area of the l th fire hawk; and r_3 and r_4 are distributed random uniformly values within the range (0, 1) used to identify the movements of prey towards the fire hawks and their respective locations. PR_q^{new} represents the q th prey's newly updated position vector (PR_q), situated within the territory of the l th fire hawk (FH_l). Additionally, prey may shift towards other fire hawk territories or attempt to escape close encounters using seeking safety outside the fire hawk domain. The following equation can accommodate these behaviors while updating their locations [39]:

$$PR_q^{new} = PR_q + (r_5 \times FH_{Alter} - r_6 \times SP), \begin{cases} l = 1, 2, \dots, n \\ q = 1, 2, \dots, r \end{cases} \quad (42)$$

where r_5 and r_6 are distributed random values uniformly within the interval (0, 1) used to calculate the movements of prey towards other fire hawks and a safe location beyond the boundaries, and FH_{Alter} denotes a fire hawk located among others in the search area. The mathematical expressions for SP_l and SP are given detailed in [39], reflecting the observation from nature of where a secure area is where several animals assemble to stay protected and protected during times of risk.

$$SP_l = \frac{\sum_{q=1}^r PR_q}{r}, \begin{cases} q = 1, 2, \dots, r \\ l = 1, 2, \dots, n \end{cases} \quad (43)$$

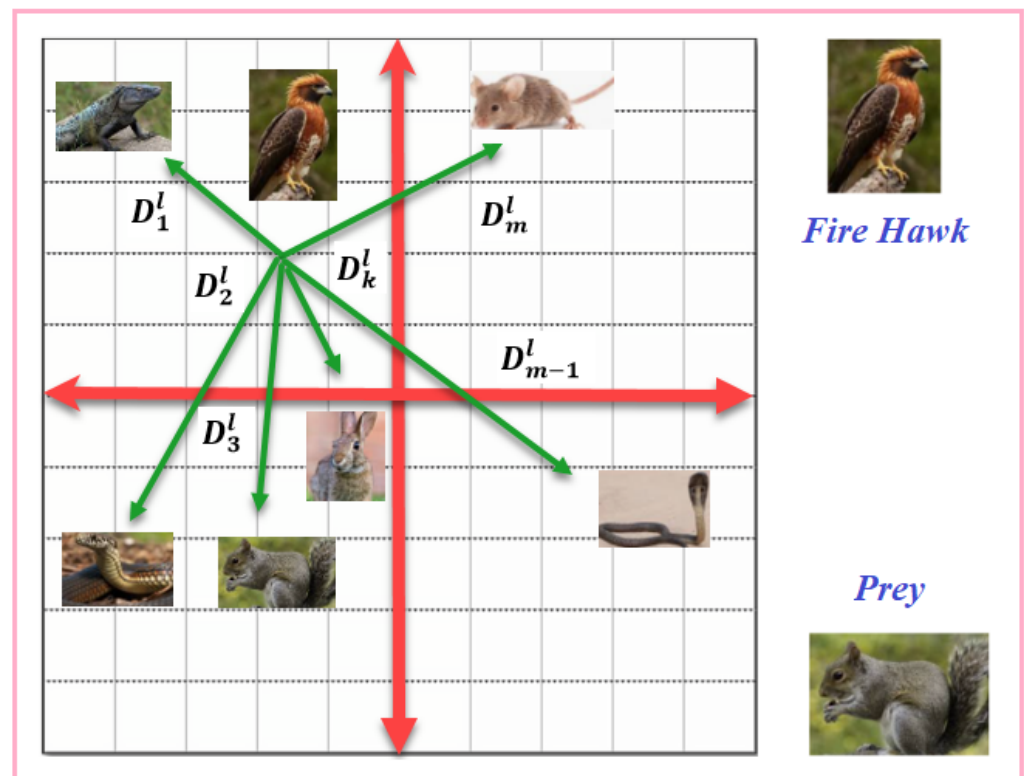


Figure 2. Diagram illustrating the total distance between Fire Hawks and targets [39].

The foundation of this approach encompasses critical elements of FHO, such as termination criteria and constraints related to potential solution boundaries. Specifically, FHO incorporates a mathematical indicator to measure the extent of variation in decision variables and may use a specified number of objective function assessments or iterations as a termination criterion.

2.4.2. Improved FHO (IFHO)

Individuals within the population that transition into the exploration phase are tasked with conducting global search operations. Consequently, their actions during this phase significantly influence the convergence rate of the Kepler optimization algorithm. In this study, a novel approach was implemented to aid individuals entering the exploration phase in improving their positions. Specifically, the golden sine method, detailed in [40], was employed. This method leverages the sine function and the golden ratio coefficient to enhance the efficiency of the search process. According to the findings presented in [40], the contraction phases associated with the golden ratio coefficient remain constant, requiring only one iteration per step. By integrating the golden ratio and sine function, optimal values can be determined more rapidly, thereby reducing the risk of becoming trapped in local optima. To incorporate the individual update mechanism for participants initiating the exploration phase using the golden sine method, the formulation of this strategy is expressed as:

$$PR_q^{new} = PR_q \times |\sin(R_1)| - R_2 \sin(R_1) \times |x_1 FH_l - x_2 SP_l| \quad (44)$$

where $X_i(t)$ and $X_i(t+1)$ denote the i th and $i+1$ th individuals at iterations t and $t+1$, respectively; t represents the current iteration number; R_1 and R_2 denote random numbers within the range $[0, 2\pi]$ and $[0, \pi]$, respectively; $P_i(t)$ signifies the current optimal individual; while x_1 and x_2 are coefficients derived from the golden ratio used to narrow the search space and guide individuals toward convergence to the optimal value. The values of x_1 and x_2 are determined by:

$$x_1 = a(1 - \tau) + b\tau \quad (45)$$

$$x_2 = a\tau + b(1 - \tau) \quad (46)$$

$$\tau = \frac{(\sqrt{5} - 1)}{2} \quad (47)$$

where τ is a fixed value that remains unchanged. The specific numerical value is given in Equation (47).

Here, a and b denote the range of search and τ represents the golden ratio, denoted as 0.618.

A flowchart illustrating the IFHO is shown in Figure 3. Additionally, Algorithm 1 outlines the pseudo-code for IFHO.

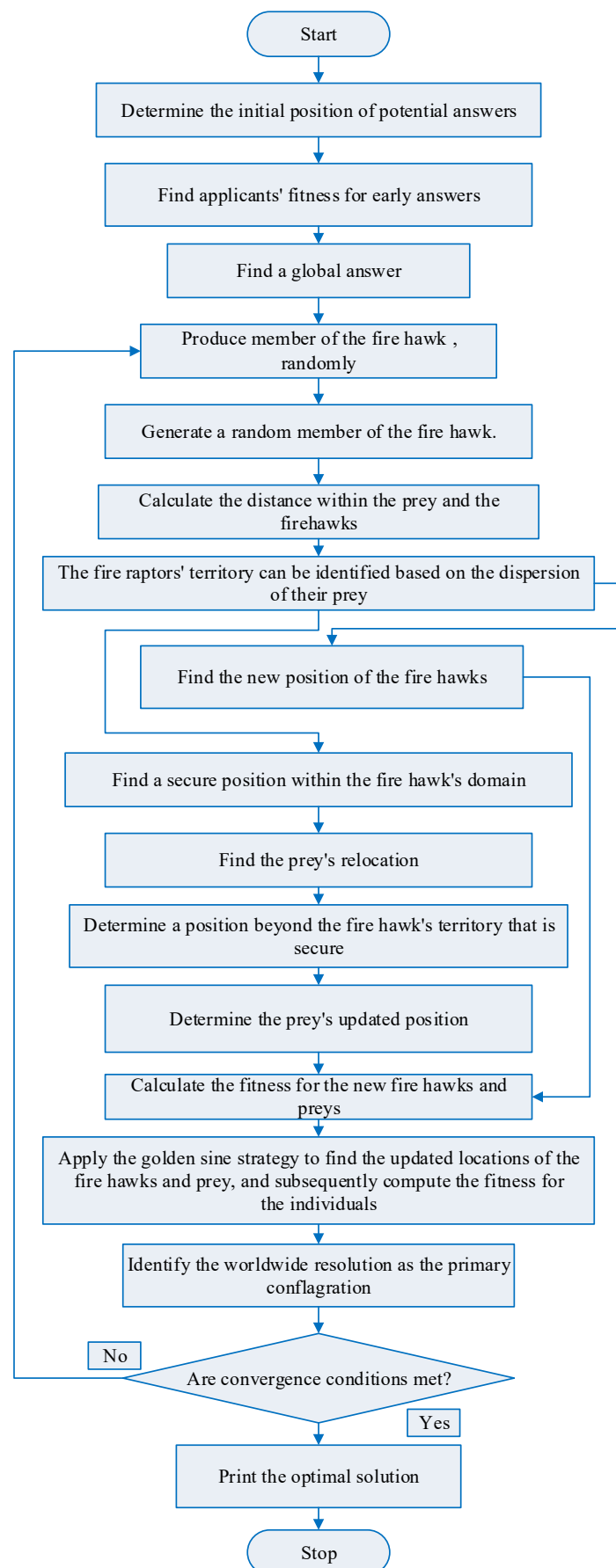


Figure 3. Flowchart of the IFHO.

Algorithm 1. IFHO

Begin the process by selecting starting points for potential solutions (X) within the search domain, considering N population. Evaluate the initial fitness scores of these candidates. Initially, identify the best solution as the global best.

while Iteration < Maximum iterations

Randomly determine the number n representing the count of fire hawks. Identify both the prey (PR) and fire hawks (FHs) within the search space. Calculate the total distance required for fire hawks to converge on their target. Distribute prey across the territory to define the domain of fire hawks.

for l = 1

Sequentially update the location of each fire hawk and subsequently the prey.

for q = 1

Identify the secure zone under the influence of the lth fire hawk. Determine the new positions of the prey. Establish a safe perimeter beyond the reach of the lth fire hawk. Determine the new positions of the prey. Evaluate the updated fitness levels of both the fire hawks and their prey.

end

end

Adjust the positioning of fire hawks based on the chaotic sequence method, reassessing fitness scores post-adjustment. Update the object position using the golden sine strategy and calculate the fitness. Conclude by re-identifying the global best solution as the primary outcome of the iteration process.

end while

Return the best solution upon completion.

end IFHO

2.4.3. FHO Implementation

The procedural steps of the IFHO for addressing the deterministic optimization framework are outlined as follows:

- (Step 1) Begin by initializing the technical and cost data for the system and its components.
- (Step 2) Generate N random values for the decision variables, ensuring they adhere to constraints.
- (Step 3) Select the values of the variables (number of PVs, WTs, HKTs, batteries, inverters, TESs, and CHP capacity) in accordance with the constraints.
- (Step 4) Calculate the total planning cost as described in (1) for the variable sets chosen in Step 3.
- (Step 5) Identify the best algorithm member with the minimum total planning cost.
- (Step 6) Update the position of decision variables using the conventional FHO method.
- (Step 7) Repeat Steps 4 and 5.
- (Step 8) Adjust the position of decision variables using the golden sine strategy based on the IFHO.
- (Step 9) Execute Steps 4 and 5 again, replacing the best solution with the previous one if better.
- (Step 10) Evaluate the convergence criteria. If met, proceed to Step 11; otherwise, return to Step 2.
- (Step 11) Terminate the optimizer and print the optimal solution (optimal number of PVs, WTs, HKTs, batteries, inverters, TESs, and CHP capacity).

2.5. Stochastic Modeling

Irradiance, wind speed, water flow, and HES demand are all uncertain in the suggested formulae described in Equations (1)–(34). As a result, these unknown parameters are modeled utilizing stochastic optimization with the $2m + 1$ PEM. The $2m + 1$ PEM employs statistical data with low approximated values of input unpredictability, as expressed by their central moments [7–9,21,22,27]. The statistical data for the outcome variables are derived using the answers acquired from these research centers. In the proposed method, multiple scenarios are created for irradiance (using a beta distribution), wind speed (using

a Weibull distribution), water flow (using a Weibull distribution), and HES load (using a normal distribution). Following this, the mean and standard deviation of the uncertainties are determined. The final scenario samples are obtained via the PEM employing the $2m + 1$ technique, where m is the number of uncertainties and $2m + 1$ is the total number of final samples. Consequently, the $2m + 1$ PEM modeling is outlined as follows:

(Step 1) The input variables number (m) is adjusted.

(Step 2) Assigning the vector of moment for the variable of output to $E(U^i) = 0$ where $E(U^i)$ is the i th vector of moment for the variable of output.

(Step 3) Setting $c = 1$ ($c = 1, 2, \dots, m$).

(Step 4) The random variable standard positions are obtained as follows:

$$\zeta_{c,j} = \frac{\lambda_{c,3}}{2} + (-1)^{3-j} \cdot \sqrt{\lambda_{c,4} - \frac{3\lambda_{c,3}^2}{4}} \quad j = 1, 2 \quad (48)$$

where $\zeta_{c,j}$ denotes the standard positions of the input variable, $\lambda_{c,3}$ refers to the skewness of the input variable z_c , and $\lambda_{c,4}$ signifies the kurtosis of the input variable z_c .

(Step 5) The z_c locations are presented by:

$$z_{c,j} = \mu_{z_c} + \zeta_{c,j} \cdot \sigma_{z_c} \quad j = 1, 2 \quad (49)$$

where $z_{c,j}$ represents the locations of input variables, μ_{z_c} is the mean of z_c , and σ_{z_c} is the standard deviation of z_c .

(Step 6) The HS optimization problem (deterministic) is implemented for z_c locations:

$$U_{c,j} = f(\mu_{z_1}, \mu_{z_2}, \dots, z_{c,j}, \dots, \mu_{z_m}) \quad j = 1, 2 \quad (50)$$

where $U_{c,j}$ is optimization (deterministic) for z_c .

(Step 7) The factors of weighting for z_c are calculated:

$$g_{c,j} = \frac{(-1)^{3-j}}{\zeta_{c,j} \cdot (\zeta_{c,1} - \zeta_{c,2})} \quad j = 1, 2 \quad (51)$$

where $g_{c,j}$ represents weight factors of z_c .

(Step 8) In this step, $E(U^i)$ is updated.

$$E(U^i) = E(U^i) + \sum_{j=1}^2 g_{c,j} (U_{c,j})^i \quad (52)$$

(Step 9) Repeat steps 4 to 8 until the input variables are incorporated.

(Step 10) The optimization problem (deterministic) is implemented considering the input variable vector randomly:

$$z_\mu = [\mu_{z_1}, \mu_{z_2}, \dots, \mu_{z_c}, \dots, \mu_{z_m}] \quad j = 1, 2 \quad (53)$$

where z_μ denotes the vector of the input variable randomly.

(Step 11) The coefficient of weight for the HS optimization problem (deterministic) presented in step 10 is outlined by:

$$g_0 = 1 - \sum_{c=1}^m \frac{1}{\lambda_{c,4} - \lambda_{c,3}^2} \quad (54)$$

where g_0 refers to the factor of weighting in the problem.

(Step 12) $E(U^i)$ is defined by:

$$E(U^i) = \sum_{c=1}^m \sum_{j=1}^2 g_{c,j} [(\mu_{z_1}, \mu_{z_2}, \dots, \mu_{z_j}, \dots, \mu_{z_m})]^i + g_0 [U(z_\mu)]^i \quad (55)$$

(Step 13) With determining the moments statistically according to the output variable randomly, mean μ_U and Standard deviation σ_U amounts are defined by:

$$\mu_U = E(U); \quad \sigma_U = \sqrt{E(U^2) - \mu_U^2} \quad (56)$$

3. Results and Discussion

3.1. System Data

The results of both deterministic and stochastic optimization of the three HESs, each incorporating different energy resources and storage, including electrical and thermal storage using the 2m + 1 PEM and IFHO, are presented in this section. The proposed methodology is applied to three cases: Case I (PV–battery–CHP–TES), Case II (WT–battery–CHP–TES), and Case III (HKT–battery–CHP–TES), as illustrated in Figure 1, utilizing real data from Espoo, Finland (60°12'20" N, 24°39'20" E). The system features peak electrical and thermal demands of 18 kW and 6 kW, respectively [41–44]. Hourly and daily load profiles of the demands are shown in Figure 4 [41–44]. Additionally, Figures 5–7 depict the daily profiles of irradiance, wind speed, and water flow [41–44]. Table 1 presents the techno-economic data for resources and storage components.

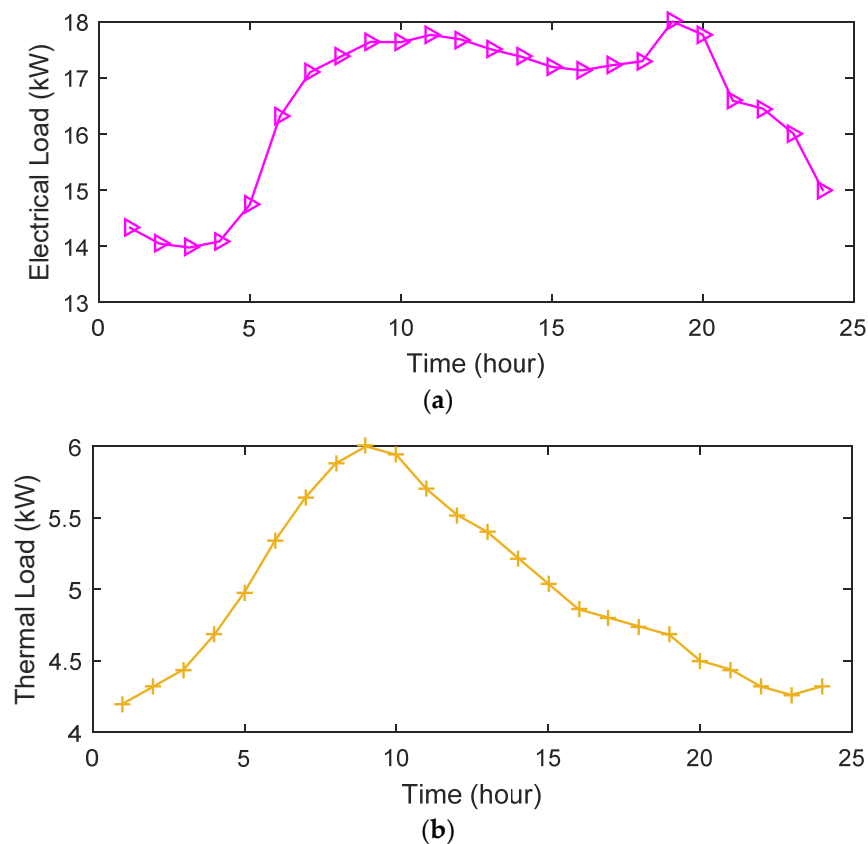


Figure 4. Profile of (a) electrical and (b) thermal load during a day.

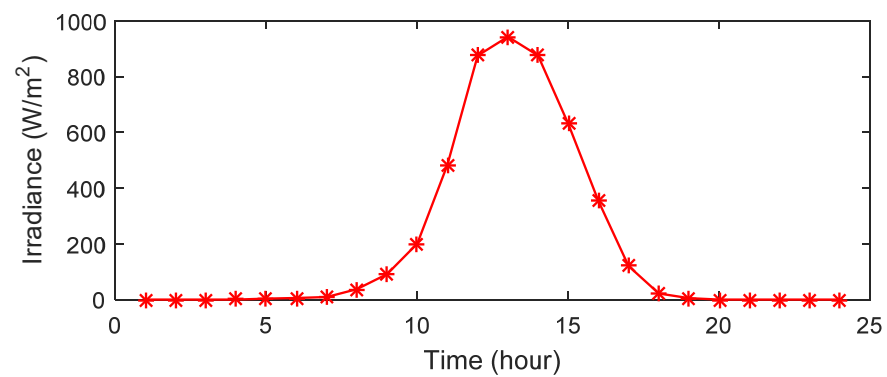


Figure 5. Profile of irradiance during a day.

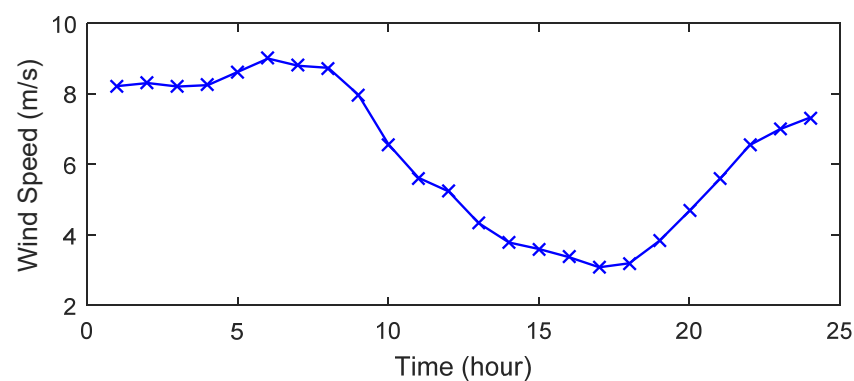


Figure 6. Profile of wind speed during a day.

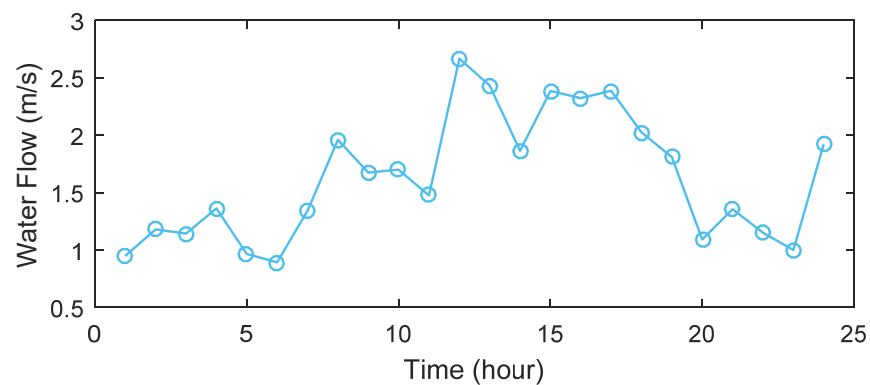


Figure 7. Profile of water flow during a day.

The proposed approach employs meteorological data and storage data from Table 1. The performance of the IFHO is compared against traditional FHO and well-known PSO methods. For the optimization algorithms, the size of population is set to 40, the maximum iterations to 300, and the number of independent runs to 25. MATLAB software Version 2015b on a PC equipped with Intel Core i7 –4510 U up to 3.1 GHz and 8 GB RAM is used to implement the proposed methodology. The effectiveness of the proposed methodology is assessed through various simulation scenarios and cases, outlined as follows.

Scenario I: Deterministic optimization (without uncertainty):

- Case I: Deterministic optimization of the PV-CHP-battery-TES system.
- Case II: Deterministic optimization of the WT-CHP-battery-TES system.
- Case III: Deterministic optimization of the HKT-CHP-battery-TES system.

Scenario II: Stochastic optimization (with uncertainty):

- Case I: Stochastic optimization of the PV-CHP-battery-TES system.
- Case II: Stochastic optimization of the WT-CHP-battery-TES system.
- Case III: Stochastic optimization of the HKT-CHP-battery-TES system.

Table 1. Data on resources and storage [14,33,41–44].

PV data:	Value	C_{M-I} (USD/year)	0
T_{STC}	25 °C	Life span (year)	10
$P_{PVrated}$ (kW)	1	HKT data:	Value
$N_{PV.max}$	50	$P_{HKT rated}$ (kW)	1
C_{I-PV} (\$)	2000	$N_{HKT.max}$	50
C_{M-PV} (USD/year)	3	C_{I-HKT} (\$)	2500
NOCT	45	C_{M-HKT} (USD/year)	4
Lifespan (year)	20	wf_{ci}, wf_{co} (m/s)	0.8, 5
κ (%)	10	wf_{rated} (m/s)	3
CF (%)	70	Lifespan (year)	20
WT data:	Value	CHP data:	Value
$P_{WT rated}$ (kW)	1	η_T (%)	38
v_{ci} (m/s)	3	η_L (%)	5
v_{rated} (m/s)	9	η_H (%)	38
v_{co} (m/s)	20	ep_c (USD/kg)	0.0037
Peak wind speed (m/s)	15	fp_c (USD/L)	1.24
$N_{WT.max}$	50	χ_c (l/kWh)	0.246
C_{I-WT} (\$)	3200	γ_c (l/kWh)	0.0845
C_{M-WT} (USD/year)	5	β_c (kg/kW)	3.25
Lifespan (year)	20	$P_{CHP.max}$ (kW)	11
Battery data:	Value	C_{I-CHP} (\$)	901.65
$E_{B.max}$ (kWh)	1.35	C_{M-CHP} (USD/year)	4
$E_{B.min}$ (kWh)	0.15	Lifespan (year)	20
η_B^c / η_B^d (%)	90	TES data:	Value
∂	0.0002	$E_{TES.max}$ (kWh)	1.5
$N_{B.max}$	100	$E_{TES.min}$ (kWh)	0.15
C_{I-B} (\$)	130	η_T^c / η_T^d (%)	78
C_{M-B} (USD/year)	0	∂	0.0002
Lifespan (year)	5	$N_{TES.max}$	10
Inverter data:	Value	C_{I-TES} (\$)	210
$P_{I.max}$ (kW)	5	C_{M-TES} (USD/year)	1.6
η_I (%)	95	Lifespan (year)	10
C_{I-I} (\$)	2000		

3.2. Deterministic Results

3.2.1. Hybrid PV-CHP-Battery-TES System

In this section, the deterministic optimization results of the PV-CHP-battery-TES system are presented using the IFHO for Scenario I, Case I, and the convergence process of IFHO, FHO, and PSO is demonstrated in Figure 8. It can be seen that the IFHO with higher convergence speed and less iteration of convergence has been able to achieve the optimal solution with a lower total cost compared to other methods. It can be seen that the improvement in the conventional FHO (in the form of IFHO) has caused the tolerance of convergence to decrease with the increase in exploration power and the optimizer is able to find the best solution faster and with a higher convergence rate.

The deterministic optimization results of the PV-CHP-battery-TES system using the IFHO are presented for Scenario I, Case I in Table 2. Also, the IFHO performance in solving the problem is compared with the conventional FHO and PSO. The obtained results demonstrate that the IFHO obtained the best solution (best variable set) with the lowest total cost compared with FHO, and PSO. As shown in Table 2, the number of PVs, batteries, TESs, and inverters are 37, 21, 6, and 4, respectively, the CHP capacity is 8.53 kW, and the total cost of the system is USD 8104.35 via the IFHO. Also, the total cost is USD 8186.26, and USD 8136.04 using FHO and PSO, respectively, confirming IFHO's superiority in achieving the lowest cost in solving the problem for Case I. Moreover, the superiority of

the recommended IFHO is confirmed compared with the other optimizers by performing a statistical analysis and obtaining better statistic criteria, such as lower mean and standard deviation values.

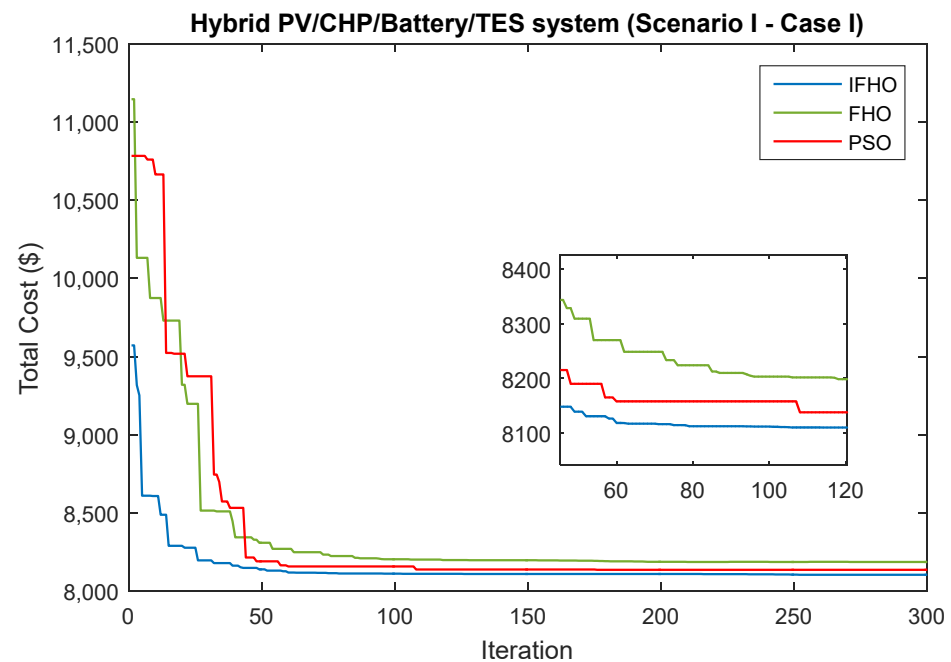


Figure 8. Convergence process of different optimizers (Scenario I, Case I).

Table 2. Best solution and cost results (Scenario I, Case I).

Item	IFHO	FHO	PSO
PV	37	39	38
Battery	21	27	24
Inverter	4	4	4
CHP Capacity (kW)	8.53	8.55	8.53
TES	6	6	6
Total Cost (USD/year)	8104.35	8186.26	8136.04
Best (USD/year)	8104.35	8186.26	8136.04
Mean (USD/year)	8135.87	8215.54	8173.41
Worst (USD/year)	8169.04	8230.18	8192.62
Standard deviation (USD/year)	347.21	375.75	361.03

Figure 9 depicts the power dispatch of energy resources and storage for PV, battery, and CHP systems, as well as the electrical demand. As can be seen, the electric load demand in different hours is given with the participation of energy production sources (PVs + CHP) and also battery storage. In the hours when the production power of PV and CHP sources is more than the demand, the extra power is injected into the batteries to charge them. Then, in the hours when the generated power by the PV + CHP sources is lower than the electrical demand, the lack in system power is supplied by discharging the batteries. Therefore, by managing the production energy and the storage battery, the required power of the electric load has been supplied. During the hours of 1:00–8:00 and 18:00–24:00, the electric load is supplied by CHP, and discharging the batteries and during these hours, the PVs are not able to produce power. However, during the hours of 8:00–18:00, the task of supplying the electric load is the responsibility of the PV + CHP sources. Due to the power generation of the PVs along with the CHP, the system has excess power during these hours that the batteries are charged, and the power of the batteries is considered negative in these hours.

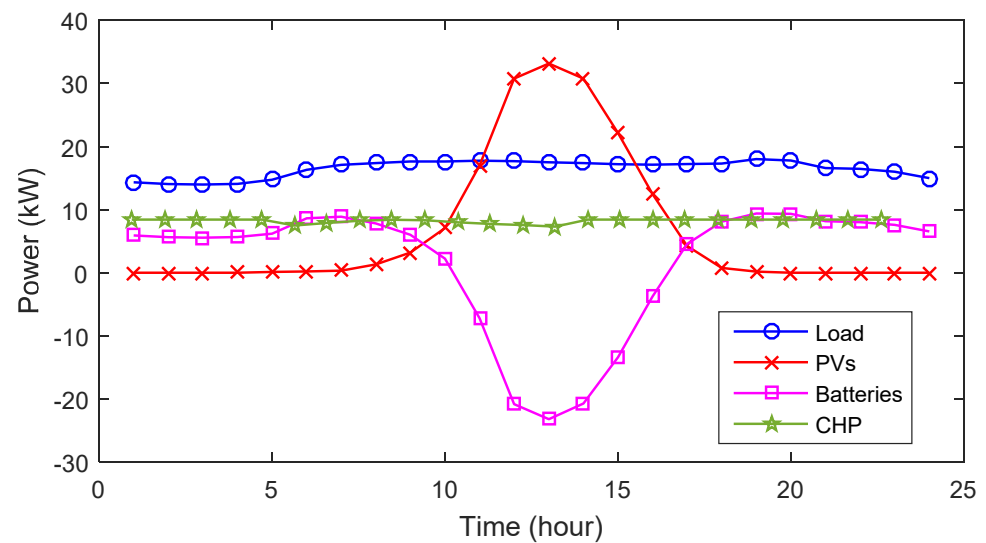


Figure 9. Power dispatch for electrical load during a day (Scenario I, Case I).

Figure 10 shows the power dispatch of the CHP + TESs to supply the thermal load during the day. As can be seen, with the participation of CHP + TESs, the thermal load has been fully supplied. During the hours when the CHP production power is more than the thermal demand (1:00–5:00 and 15:00–24:00), the CHP excess thermal power is stored in the TESs, and when the CHP production power is insufficient to supply the thermal load during 5:00–15:00, the thermal load shortage is compensated by the TESs. Therefore, it can be seen that the presence of TESs along with the CHP is able to implement thermal scheduling for reliable supply of the thermal load and the system is not able to provide sufficient and continuous thermal load without using thermal storage.

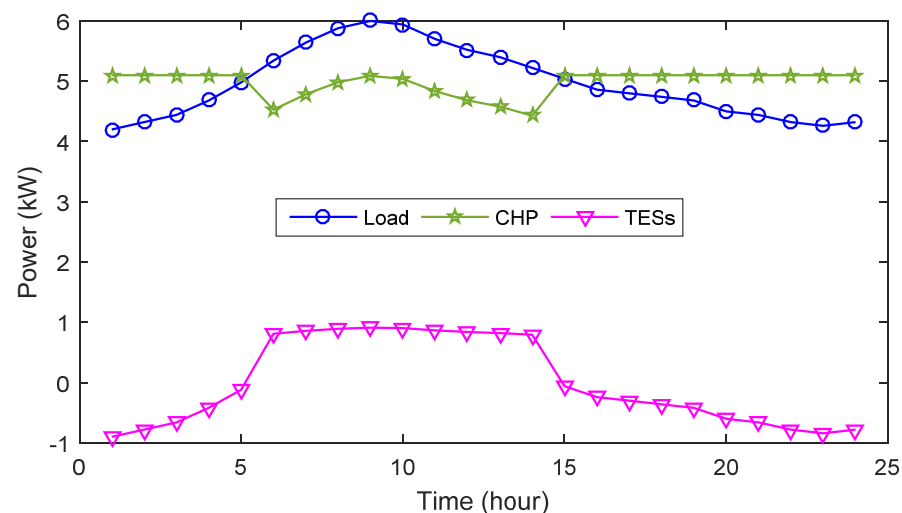


Figure 10. Power dispatch for thermal load during a day (Scenario I, Cases I–III).

3.2.2. Hybrid WT–CHP–Battery–TES System

The deterministic optimization results for the WT–CHP–battery–TES system are given using the IFHO for Scenario I, Case II. Figure 11 illustrates the convergence processes of IFHO, conventional FHO, and PSO. The results reveal that IFHO achieves the optimal answer with a lower total cost, higher convergence rate, and fewer iterations compared to the other methods. The enhancement of the conventional FHO into IFHO significantly reduces the convergence tolerance while increasing exploration capabilities. This improvement allows the optimizer to identify the best solution more swiftly and efficiently. Additionally,

the robustness and adaptability of IFHO are evident, as it consistently outperforms the traditional methods, demonstrating its superiority compared with the basic FHO and PSO.

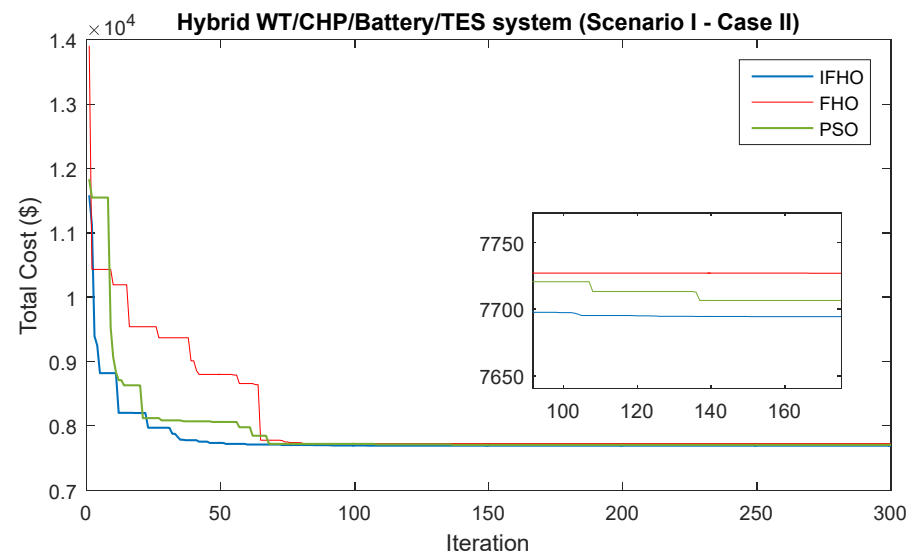


Figure 11. Convergence process of different optimizers (Scenario I, Case II).

Table 3 presents the deterministic optimization outcomes of the WT–CHP–battery–TES system for Scenario I, Case I, using the IFHO. The performance of IFHO in solving the problem is compared with that of conventional FHO and PSO. The results indicate that IFHO achieves the best solution with the lowest total cost compared to FHO and PSO. Specifically, Table 3 shows that the optimal configuration includes 16 wind turbines (WTs), 64 batteries, 6 TESs, and 3 inverters, with a CHP capacity of 8.42 kW when optimized using IFHO. The total system cost is calculated as USD 7694.26 using IFHO, USD 7726.71 with FHO, and USD 7706.47 with PSO. These outcomes confirm the superiority of IFHO in minimizing costs.

Table 3. Best solution and cost results (Scenario I, Case II).

Item	IFHO	FHO	PSO
WT	16	17	16
Battery	42	47	44
Inverter	3	3	3
CHP Capacity (kW)	8.42	8.44	8.43
TES	6	6	6
Total Cost (USD/year)	7694.26	7726.71	7706.47
Best (USD/year)	7694.26	7726.71	7706.47
Mean (USD/year)	7726.55	7726.55	7734.28
Worst (USD/year)	7749.31	7765.36	7758.12
Standard deviation (USD/year)	288.64	311.93	295.40

Moreover, statistical analysis reinforces the superiority of IFHO over other optimization methods, as it achieves better statistical criteria, such as lower mean and standard deviation values. This demonstrates that IFHO not only finds the optimal solution more effectively but also exhibits greater robustness and consistency across different runs. The enhanced exploration and exploitation capabilities of IFHO contribute to its superior performance, making it a more reliable choice for complex optimization problems in energy systems.

Figure 12 illustrates the power dispatch of various energy resources and storage systems, including wind turbines (WTs), batteries, combined heat and power (CHP), and

the corresponding electrical demand. The graph shows that the electric load demand at different hours is met through the combined efforts of energy production sources (WTs and CHP) and battery storage. During periods when the power generated by WTs and CHP exceeds the demand, the surplus energy is used to charge the batteries. Conversely, during times when the generated power from WTs and CHP is insufficient to meet the electrical demand, the shortfall is compensated based on the discharging the batteries. This effective management of energy production and storage ensures that the electric load requirements are consistently met. Specifically, from 10:00 to 22:00, the electric load is supplied by a combination of WTs, CHP, and discharging batteries. However, from 1:00 to 10:00 and from 22:00 to 24:00, the system generates excess power, which is stored in the batteries (charging mode), indicated by negative values for battery power during these hours. This approach not only optimizes the utilization of available resources but also enhances the reliability and efficiency of the power supply. By strategically managing the generation and storage of energy, the system ensures a stable and continuous supply of electricity to meet varying demand levels throughout the day.

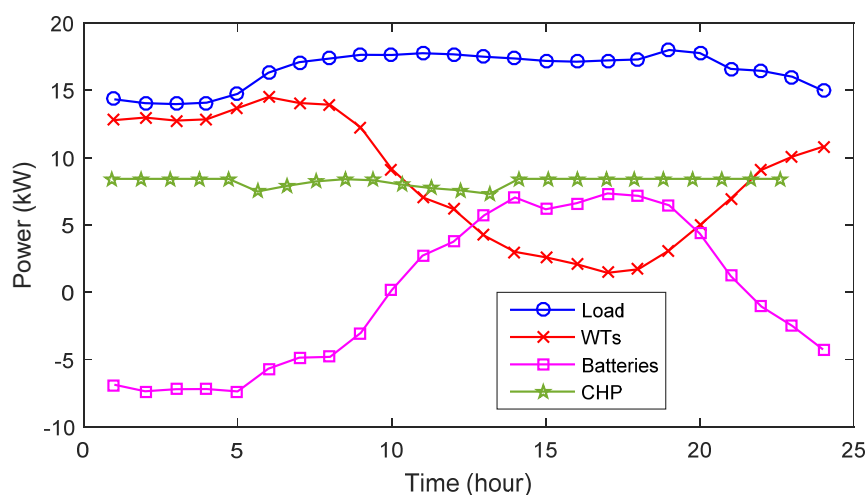


Figure 12. Power dispatch for electrical load during a day (Scenario I, Case II).

For Case II, the power dispatch of CHP + TES to meet the thermal load throughout the day follows the same pattern as shown in Figure 10 for Case I. Since the primary difference between Cases I, II, and III is the type of renewable source used, the system's performance in supplying the heat load relies entirely on CHP and heat storage. This approach is consistent across all cases and is illustrated in Figure 10.

3.2.3. Hybrid HKT-CHP-Battery-TES System

In this section, we present the deterministic optimization results for the HKT-CHP-battery-TES system using IFHO for Scenario I, Case III. Additionally, the convergence processes of IFHO, conventional FHO, and PSO are illustrated in Figure 13. The results demonstrate that IFHO achieves the optimal solution at a lower total cost, with higher convergence speed and fewer iterations, compared to the other methods. The transformation of conventional FHO into IFHO has effectively reduced the tolerance of convergence by enhancing exploration capabilities. This improvement enables the optimizer to identify the best solution more rapidly and with a higher convergence rate. Furthermore, the improved performance of IFHO highlights its superior capability and efficiency in solving HKT-CHP-battery-TES system optimization compared with FHO and PSO.

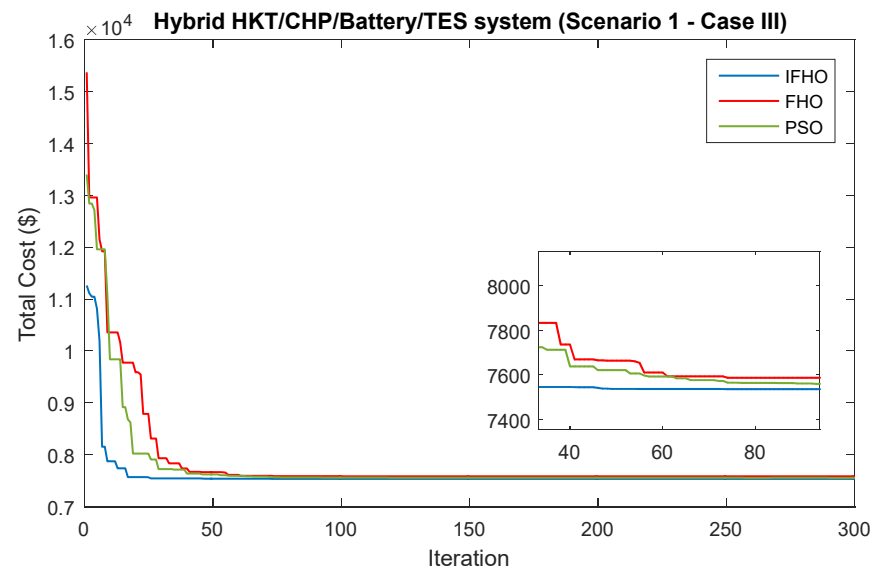


Figure 13. Convergence process of different optimizers (Scenario I, Case III).

The deterministic optimization results of the HKT–CHP–battery–TES system using IFHO are presented for Scenario I, Case III in Table 4. The performance of IFHO in solving the problem is also compared with conventional FHO and PSO. The results demonstrate that IFHO achieves the best solution (optimal variable set) at the lowest total cost compared to FHO and PSO. According to Table 4, the system configuration includes 27 HKTs, 15 batteries, 6 TESs, and 4 inverters, with a CHP capacity of 8.42 kW optimized by IFHO. The total system cost is calculated as USD 7536.08 using IFHO, USD 7584.37 using FHO, and USD 7552.11 using PSO. These outcomes confirm the superior cost-effectiveness of IFHO in solving the problem. Furthermore, statistical analysis affirms the superiority of IFHO over other optimizers, as it achieves better statistical values such as lower mean and standard deviation.

Table 4. Best solution and cost results (Scenario I, Case III).

Item	IFHO	FHO	PSO
HKT	27	28	27
Battery	15	27	14
Inverter	4	4	4
CHP Capacity (kW)	8.42	8.42	8.44
TES	6	6	6
Total Cost (USD/year)	7536.08	7584.37	7552.11
Best (USD/year)	7536.08	7584.37	7552.11
Mean (USD/year)	7560.24	7625.48	7586.24
Worst (USD/year)	7577.10	7642.77	7610.62
Standard deviation (USD/year)	327.38	385.46	351.55

Figure 14 illustrates the power distribution of energy resources and storage components such as HKTs, batteries, and CHP alongside the electrical demand. It shows how the electric load demand across different hours is met through the combined contributions of energy production sources (HKTs + CHP) and battery storage. During periods when the HKTs and CHP generate more power than the load, the surplus electricity is stored in batteries for charging. Conversely, when the generated power from HKTs + CHP is insufficient to meet the electrical demand, the batteries discharge to supplement the system power. This effective management of energy production and battery storage ensures that the electric load requirements are consistently fulfilled. Specifically, from 1:00 to 11:00 and from 18:00 to 24:00, the electric load is supplied by HKTs + CHP, with additional support

from battery discharge. However, from 11:00 to 18:00, due to ample power generation from HKTs and CHP, the system generates excess electricity. During these hours, the surplus power charges the batteries, resulting in negative battery power values.

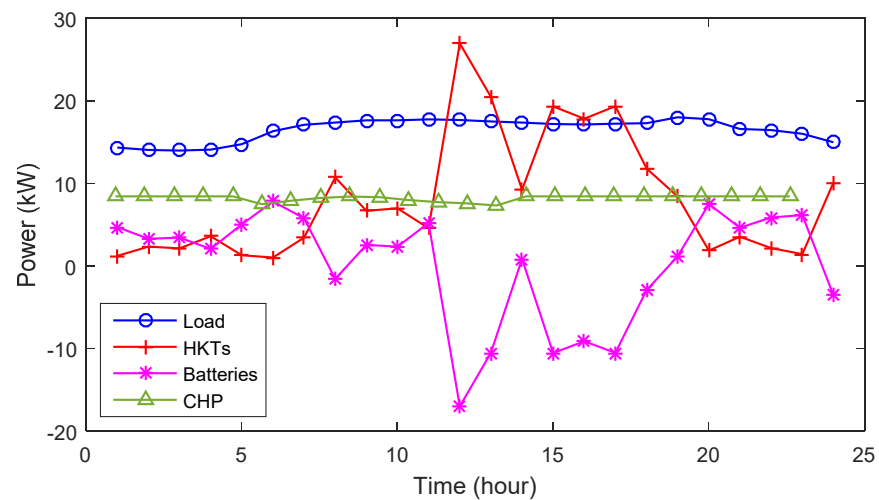


Figure 14. Power dispatch for electrical load during a day (Scenario I, Case III).

In Case III, the strategy for dispatching power from CHP and TES to meet the thermal load during the day mirrors that depicted in Figure 10 for Case I. The primary distinction among Cases I through III lies in their renewable energy sources. Consequently, the system's capability to supply the heat load depends entirely on the CHP and thermal energy storage (TES), which remains consistent across all cases and aligns with the depiction in Figure 10.

3.2.4. Comparison of the Deterministic Results

Table 5 and Figure 15 compare the performance of different scenarios in Scenario I using IFHO, FHO, and PSO. It is evident that Case III, employing the hybrid HKT–CHP–battery–TES system, achieved the lowest planning cost. In contrast, Case I, which utilized the hybrid PV–CHP–battery–TES system, incurred the highest planning cost across all algorithms. These results highlight the cost-effectiveness of integrating HKTs into HESs, while systems incorporating photovoltaic sources tend to have higher design costs. Furthermore, Case III demonstrated a planning cost reduction of 7.01% and 2.05% compared to Cases I and II, respectively. This underscores the superior economic performance of the HES with HKTs.

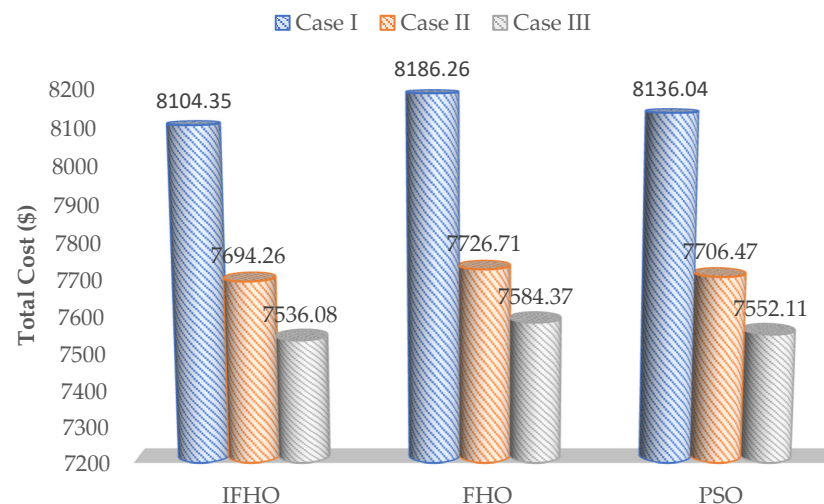


Figure 15. Comparison of the total cost in different cases using different optimizers (Scenario I, Cases I–III).

Table 5. Comparison of the planning cost for different scenario using the IFHO.

System	Case	IFHO	FHO	PSO
Hybrid PV–CHP–Battery–TES system	I	8104.35	8186.26	8136.04
Hybrid WT–CHP–Battery–TES system	II	7694.26	7726.71	7706.47
Hybrid HKT–CHP–Battery–TES system	III	7536.08	7584.37	7552.11

3.3. Stochastic Results

This section presents the stochastic optimization results for Cases I–III using the 2m + 1 PEM and IFHO in Scenario II. Tables 6–8 summarize the best solutions and cost outcomes for each case. As shown in Table 6, in Case I, considering uncertainties in the stochastic model, the number of PV sources and batteries increased, and the CHP capacity rose from 8.53 kW to 8.55 kW, resulting in a total system cost increase from USD 8104.35 to USD 8451 (4.28%). Similarly, Table 7 shows that for Case II, in the stochastic model uncertainties, the WTs and batteries number increased, and the CHP capacity increased from 8.42 kW to 8.47 kW, leading to a total cost increase from USD 7694.26 to USD 7982.50 (3.75%). Furthermore, as shown in Table 8 and incorporating the stochastic model, Case III saw an increase in the number of HKT sources and batteries and the CHP capacity increased from 8.44 kW to 8.46 kW, resulting in a planning cost increase from USD 7536.08 to USD 7805.23 (3.57%).

Table 6. Best solution and cost results (Scenario II, Case I).

Item	Scenario II, Case I (Stochastic)	Scenario I, Case I (Deterministic)
PV	40	37
Battery	26	21
Inverter	4	4
CHP Capacity (kW)	8.58	8.53
TES	6	6
Total Cost (USD/year)	8451.17	8104.35
Best (USD/year)	8451.17	8104.35
Mean (USD/year)	8477.53	8135.87
Worst (USD/year)	8485.60	8169.04
Standard deviation (USD/year)	372.08	347.21

Table 7. Best solution and cost results (Scenario II, Case II).

Item	Scenario II, Case II (Stochastic)	Scenario I, Case II (Deterministic)
WT	18	16
Battery	47	42
Inverter	4	3
CHP Capacity (kW)	8.47	8.42
TES	6	6
Total Cost (USD/year)	7982.78	7694.26
Best (USD/year)	7982.78	7694.26
Mean (USD/year)	7756.04	7726.55
Worst (USD/year)	7795.37	7749.31
Standard deviation (USD/year)	311.29	288.64

Thus, as depicted in Table 9 and Figure 16, the costs for Cases I–III have increased by 4.28%, 3.75%, and 3.57%, respectively, when considering the stochastic optimization model compared to the deterministic model. Tables 6–8 also illustrate that the production quantities and storage levels differ between the deterministic and stochastic models. This indicates that under conditions of uncertainty, the production from sources and the battery

storage levels do not adequately respond to the load. Therefore, the stochastic model proves to be a reliable approach due to its ability to account for uncertainties.

Table 8. Best solution and cost results (Scenario II, Case III).

Item	Scenario II, Case III (Stochastic)	Scenario I, Case III (Deterministic)
HKT	30	27
Battery	18	15
Inverter	4	4
CHP Capacity (kW)	8.46	8.44
TES	6	6
Total Cost (USD/year)	7805.23	7536.08
Best (USD/year)	7805.23	7536.08
Mean (USD/year)	7837.45	7560.24
Worst (USD/year)	7855.01	7577.10
Standard deviation (USD/year)	334.63	327.38

Table 9. Comparison of the planning cost for different scenarios using the IFHO.

System	Case	Total Cost (USD/year), Scenario II
Hybrid PV–CHP–Battery–TES system	I	4.28
Hybrid WT–CHP–Battery–TES system	II	3.75
Hybrid HKT–CHP–Battery–TES system	III	3.57

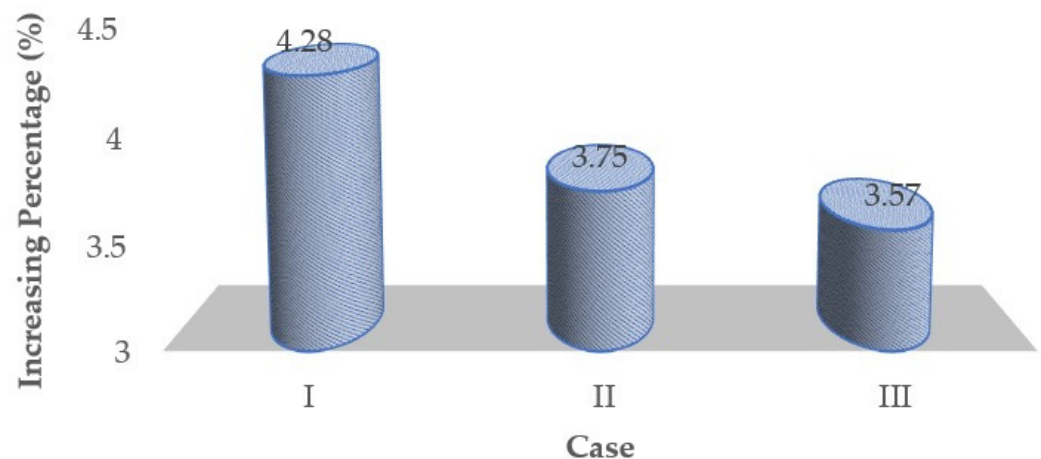


Figure 16. Increasing percentage of the total cost in Scenario II compared with Scenario I (Scenario II, Cases I–III).

4. Conclusions

In this study, a stochastic framework was recommended for the optimization of three cases (Case I–III) on an HES including PVs, WTs, HKTs, CHP, and TESs to supply the electrical and thermal demand considering the generation and load uncertainties using the $2m + 1$ PEM, and IFHO for minimizing the planning cost. The deterministic and stochastic findings of the research are listed as follows.

- The deterministic analysis, without uncertainties, revealed that Case III (HKT–CHP–battery–TES) achieved the lowest planning cost, while Case I (PV–CHP–battery–TES) had the highest. The planning costs for Cases I–III were USD 8104.35, USD 7694.26, and USD 7536.08, respectively, highlighting the superior performance of Case III.
- The effectiveness of IFHO was assessed against conventional FHO and PSO in deterministic optimization. The results demonstrated that IFHO achieved the best solution

with faster convergence, fewer iterations, and lower planning costs compared to other methods. This improvement, using the golden sine strategy, significantly improved FHO's performance in solving problems and achieving lower planning costs.

- Both deterministic and stochastic results indicated that Case III (hybrid HKT–CHP–battery–TES) achieved the lowest planning cost and reduced costs by 7.01% and 2.05%, respectively, compared to Cases I and II when using IFHO.
- Stochastic outcomes incorporating the 2m + 1 PEM model showed an increase in the number of energy resources, storage capacities, and CHP capacities compared to the deterministic model, which does not account for uncertainty. Specifically, planning costs increased by 4.28%, 3.75%, and 3.57% for Cases I–III compared to the deterministic model.
- A comparison between deterministic and stochastic outcomes revealed discrepancies in the generation capacities of resources, storage levels, and CHP capacities between the two models. These discrepancies make it clear that deterministic values do not adequately respond to load uncertainties, highlighting the reliability of stochastic models in uncertain conditions.
- Future research is recommended to explore stochastic optimization of hybrid fuel cell–CHP–battery–TES to meet electrical and thermal demands, considering uncertainty. This proposed study will evaluate the incorporation of multi-energy storage based on hydrogen and battery storage to evaluate planning costs and optimize results.

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