Article

Cost-Eff ective Planning of Hybrid Energy Systems Using Improved Horse Herd Optimizer and Cloud Theory under Uncertainty

Ali S. Alghamdi

Department of Electrical Engineering, College of Engineering, Majmaah University, Al-Majmaah 11952, Saudi Arabia; aalghamdi@mu.edu.sa

Abstract: In this paper, an intelligent stochastic model is recommended for the optimization of a hybrid system that encompasses wind energy sources, battery storage, combined heat and power generation, and thermal energy storage (Wind/Battery/CHP/TES), with the inclusion of electric and thermal storages through the cloud theory model. The framework aims to minimize the costs of planning, such as construction, maintenance, operation, and environmental pollution costs, to determine the best configuration of the resources and storage units to ensure efficient electricity and heat supply simultaneously. A novel meta-heuristic optimization algorithm named improved horse herd optimizer (IHHO) is applied to find the decision variables. Rosenbrock’s direct rotational technique is applied to the conventional horse herd optimizer (HHO) to improve the algorithm’s performance against premature convergence in the optimization due to the complexity of the problem, and its capability is evaluated with particle swarm optimization (PSO) and manta ray foraging optimization (MRFO) methods. Also, the cloud theory-based stochastic model is recommended for solving problems with uncertainties of system generation and demand. The obtained results are evaluated in three simulation scenarios including (1) Wind/Battery, (2) Wind/Battery/CHP, and (3) Wind/Battery/CHP/TES systems to implement the proposed methodology and evaluate its effectiveness. The results show that scenario 3 is the best configuration to meet electrical and thermal loads, with the lowest planning cost (12.98% less than scenario 1). Also, the superiority of the IHHO is proven with more accurate answers and higher convergence rates in contrast to the conventional HHO, PSO, and MRFO. Moreover, the results show that when considering the cloud theory-based stochastic model, the costs of annual planning are increased for scenarios 1 to 3 by 4.00%, 4.20%, and 3.96%, respectively, compared to the deterministic model.

Keywords: hybrid energy systems; stochastic modeling; meta-heuristic optimization; cloud theory-based model; renewable energy integration; uncertainty analysis

1. Introduction

In remote regions with limited power grid connectivity, self-sustaining energy systems are crucial for meeting energy demands [1]. These areas often have diverse energy needs, requiring the integration of multiple energy sources and storage solutions [2,3]. Renewable energy sources (RESs) like wind turbines and photovoltaic panels are preferred due to their economic viability and minimal environmental footprint [4]. Combined heat and power (CHP) systems are also suitable for areas with varied energy consumption needs [5,6]. However, the variability in daily power output may not perfectly match the fluctuating energy demand, necessitating the use of storage solutions [7,8]. A well-structured and sustainable hybrid energy system requires meticulous long-term planning to
determine the optimal quantity and size of resources and storage devices [9,10]. Acknowl-
ledging uncertainties, particularly in load and RES output predictions, is essential for fos-
tering reliable planning and operational resilience [11,12].

The input discusses various studies and approaches that have been undertaken to
optimize and plan stand-alone energy systems that integrate different energy sources and
storage solutions [13–31]. These studies utilize different optimization algorithms such as
artificial bee colony [13], harmony search [15], elephant herd optimization [18], water
wave optimization [21], and particle swarm optimization (PSO) [23], among others. The
goal of these studies is to minimize operating costs [14,18,21,26], improve voltage condi-
tions [14], reduce load loss and emissions [18,19], and ensure system reliability [24,28,31].

Some studies focus on specific components of hybrid energy systems, such as photovoltaic
(PV) panels, wind turbines, batteries, and electric vehicles, while others consider the over-
all system design and operation. They also consider uncertain parameters [14,25,26,29]
and demand response [21,25] in their optimization models [25,26]. To address uncertainty,
different methods are employed, including Monte Carlo Simulation (MCS), analytical ap-
proaches, and approximate approaches [32,33]. MCS is widely used due to its accuracy,
but it can be computationally demanding. Analytical and approximate approaches offer
simplified models with lower computational costs. The point estimate method (PEM) is a
prominent technique in this group. The input suggests a new framework that integrates
cloud model (CM) theory for more efficient modeling of uncertainties in hybrid energy
systems [34,35]. The CM approach combines randomness and fuzziness to represent un-
certainty comprehensively. It can handle incomplete or ambiguous information and man-
age uncertainties arising from imperfect data or vague knowledge. The CM approach pro-
vides more accurate and realistic modeling of uncertain phenomena and yields intuitive
and interpretable results [34]. It is also computationally efficient, making it suitable for
real-time or iterative applications [35]. Overall, these studies and approaches contribute
to the optimization and planning of stand-alone energy systems by considering different
energy sources, storage solutions, and uncertain parameters. They aim to minimize costs,
improve system performance, and ensure reliability while taking into account the com-
plexities and uncertainties inherent in these systems.

The research reveals several defects in the planning and optimization of hybrid sys-
tems. Many prior studies neglect thermal load considerations in favor of optimizing en-
ergy resources and storage for supplying electrical energy. Although CHP systems have
gained interest for boosting power generation efficiency, they have received scant at-
tention in hybrid energy system planning research. Additionally, there is a deficiency in in-
corporating uncertainty modeling into hybrid systems optimization and planning. Det-
eministic planning may prove insufficient in mitigating uncertainty-induced fluctuations.
In conclusion, existing studies indicate that addressing optimization problems with a sin-
gle algorithm is not feasible, underscoring the necessity for innovative algorithms guided
by the “no free lunch” theory.

A strategy for optimizing and planning a hybrid energy system (Wind/Bat-
tery/CHP/TES) that combines wind energy sources, battery storage, CHP generation, and
thermal storage is presented in this paper. Minimizing planning expenses, including in-
vestment, operation, maintenance, and emissions, is the objective. In order to fulfill elec-
trical load requirements, wind turbines are employed, whereas combined heat and power
systems provide thermal loads. To compensate for differences between electrical and ther-
mal load demands, batteries and thermal energy storage (TES) are utilized. To address
uncertainties, a stochastic framework based on cloud model theory is proposed. By utiliz-
ing the improved horse herd optimizer (IHHO), premature convergence issues that
plague conventional HHO [36] are circumvented when determining decision variables.
The direct rotational (RDR) method [37] of Rosenbrock is utilized to reduce the complexity
of problems.
The remaining portion of this research is structured as follows: The research methodology is explained in Section 2, which includes a description of the hybrid system, component modeling, problem formulation, and cloud theory. In Section 3, the proposed improved optimizer and its application for problem solving are introduced. Section 4 presents the simulation results. Finally, Section 5 concludes the paper.

2. Research Methodology

2.1. Overview of the Research Approach

This research aims to optimize the sizes and operations of a hybrid energy system comprising wind turbines, CHP units, electric battery storage, and TES. The methodology involves system description, detailed component modeling, problem formulation, and stochastic modeling using cloud theory to address uncertainties.

2.2. System Description

The proposed hybrid energy system, illustrated in Figure 1, includes the following:

- WT: Provides renewable electricity.
- CHP: Generates both electricity and thermal energy, prioritizing thermal load due to cost-effectiveness and low emissions.
- Electric battery storage: Balances electricity supply and demand.
- TES: Manages surplus and deficit in thermal energy from CHP.
- Inverter: Utilized with the battery system to facilitate the connection of batteries to the AC bus, enabling efficient energy storage and discharge.

In the AC bus, the wind turbine, CHP, and battery are employed to supply power. For the thermal load, CHP and TES provide the necessary energy. Priority is given to CHP and wind turbines in supplying electric load due to their low costs of emissions and operation. CHP is particularly emphasized in meeting thermal load requirements. Within this system, CHP concurrently generates thermal and active power. The battery serves to bridge the gap between electric demand requirements daily and the power produced by CHP and the wind turbine. The operational framework of the hybrid Wind/Battery/CHP/TES energy system is outlined as follows: CHP takes precedence in supplying the heat load, followed by the utilization of TES to match the heat demand and the CHP heat power. In cases where the CHP thermal power exceeds (falls short of) the thermal demand, TES functions as a charging (discharging) state. CHP and wind units are the original resources for the electrical demand supply, while the batteries serve to bridge any disparities within the daily electrical demand and the combined CHP and WT power. If the overall production of these units exceeds (falls short of) the electrical demand, the batteries function in a charge (discharge) state.
2.3. Component Models

Each component is modeled here to capture its behavior and interaction within the hybrid system.

2.3.1. WT Model

The overall active power generated by wind turbines during time $\tau$ for scenario $\omega$ varies according to different wind speed categories, as specified by [15,29].

\[
P_{WT}(\tau, \omega) = \begin{cases} 
0, & \text{if } v_{ci} \leq v_{r} \leq v_{co} \text{ and } v(\tau, \omega) \leq v_{r} \\
\frac{v(\tau, \omega)-v_{r}}{v_{r}-v_{ci}} n_{WT} p_r, & \text{if } v_{cut-in} \leq v(\tau, \omega) \leq v_{r} \\
\frac{v(\tau, \omega)-v_{r}}{v_{r}-v_{co}} n_{WT} p_r, & \text{if } v_{r} \leq v(\tau, \omega) \leq v_{co}
\end{cases}
\]

where $p_r$ denotes the nominal power of each wind unit, while $v_{ci}$, $v_{co}$, and $v_{r}$ indicate the cut-in, cut-out, and rated wind speeds, respectively. $n_{WT}$ denotes the total number of wind units, while $\bar{n}_{WT}$ refers to the upper allowable number of wind turbines within the hybrid system.

2.3.2. CHP Model

In this research, CHP is given precedence in meeting the heat load requirement [38,39]. However, to minimize operational expenses and environmental impact, thermal energy storage (TES) [2,40] is integrated with CHP. Thus, the CHP power ($P_c$) at time $\tau$ and scenario $\omega$ is determined as a decision variable, guided by the problem target and constraints. The allowable limit of $P_c$ change is calculated by

\[
P_c(\tau, \omega) \in \left[ 0, P_{c_{\text{max}}} \right]
\]

where $P_{c_{\text{max}}}$ is the maximum limit of the CHP output power.

The CHP thermal power ($H_c$) is computed as follows [38,39]:

\[
H_c(\tau, \omega) = \frac{(1-\eta_T-\eta_L) \eta_H}{\eta_T} P_c(\tau, \omega)
\]

where $\eta_T$, $\eta_L$, and $\eta_H$ are the wind unit, loss, and heating part efficiencies, respectively.
The allowable change in the $HC_t$ is as follows:

$$H_C(t, \omega) \in \left[0, \frac{(1 - \eta_t - \eta_i)}{\eta_t} \eta_i \times P_{C}^{\text{max}}\right]$$

(5)

The annual cost of CHP is calculated by

$$FC_C = 365 \times CF \times \sum_{i=1}^{n} \sum_{\omega=1}^{\omega} \pi(\omega) \times f_{PC} \times \left(\chi_C P_{C}^{\text{max}} + \gamma_C P_C(t, \omega)\right)$$

(6)

where $f_{PC}$ is the cost of CHP fuel consumption, $\chi_C$ and $\gamma_C$ are the CHP fuel consumption coefficients, $\pi$ is the scenario occurrence probability, and $n_o$ is the scenario number. $CF$ indicates the coincidence factor.

The CHP emission annual cost is defined as follows:

$$EC_C = 365 \times CF \times \sum_{i=1}^{n} \sum_{\omega=1}^{\omega} \pi(\omega) \times e_{PC} \times \beta_C P_C(t, \omega)$$

(7)

where $e_{PC}$ is the penalty price of the emissions. The coefficient $\beta_C$ is the total of the coefficients of NOx, CO2, and SO2 emissions [39,40].

Finally, the size limit of the CHP is calculated by

$$P_{C}^{\text{max}} \in [0, P_C]$$

(8)

where $P_C$ is the upper installable capacity of the CHP.

### 2.3.3. TES Model

If the CHP thermal energy generated during time $\tau$ and for scenario $\omega$ exceeds the thermal demand ($HL$), then the thermal energy storages (TESs) will function in charge mode. The saved TES ($ET$) energy at time $\tau$ for scenario $\omega$ can be determined by [2,40]

$$E_T(t, \omega) = (1 - \vartheta) \times E_T(t - 1, \omega) + \eta_T \times (H_C(t, \omega) - H_L(t, \omega)) \quad \forall H_C(t, \omega) > H_L(t, \omega)$$

(9)

where $\eta_T$ denotes the TES charging efficiency, and $\vartheta$ is the hourly rate of discharge [18].

When there is no heat output from the CHP to match the heat load, the TESs discharge their stored energy. In such instances, the calculation for the energy saved in $E_T$ at time $\tau$ is as follows:

$$E_T(t, \omega) = (1 - \vartheta) \times E_T(t - 1, \omega) - \frac{1}{\eta_T} \times (H_L(t, \omega) - H_C(t, \omega)) \quad \forall H_C(t, \omega) < H_L(t, \omega)$$

(10)

where $\eta_T'$ refers to the efficiency of TES discharge.

The restriction on the stored energy capacity in TESs is specified as follows:

$$E_T(t, \omega) \in [n_T E_T - n_T \bar{E}_T]$$

(11)

where $E_T$ and $\bar{E}_T$ are the lower and upper energy storage capacities in TESs, respectively. $n_T$ denotes the upper number of TESs allowed for installation and is determined by

$$n_T \in \{1, 2, ..., \bar{n}_T\}$$

(12)

where $\bar{n}_T$ is the upper value of the TES number within the hybrid system.

### 2.3.4. Battery Model

If the combined CHP and WT power during time $\tau$ for scenario $\omega$ exceeds the electrical demand ($P_E$), the excess active power output is saved in batteries [29,30]. Thus, the calculation for the energy saved in the battery ($EB$) at hour $\tau$ is as follows:
\[ E_b(\tau, \omega) = (1 - \delta) \times E_b(\tau - 1, \omega) + \eta_{c} \times \eta_{I} \left( P_c(\tau, \omega) + P_{WT}(\tau, \omega) - P_b(\tau, \omega) \right) \]
\[ \forall P_c(\tau, \omega) + P_{WT}(\tau, \omega) > P_b(\tau, \omega) \]  
(13)

In cases where the electrical load surpasses the CHP and wind unit total, batteries provide a deficit in active power requirements. Hence, the computation for \( E_b \) is as follows:

\[ E_b(\tau, \omega) = (1 - \delta) \times E_b(\tau - 1, \omega) - \frac{1}{\eta_{c} \times \eta_{I}} \left( P_c(\tau, \omega) - P_c(\tau, \omega) - P_{WT}(\tau, \omega) \right) \]
\[ \forall P_c(\tau, \omega) + P_{WT}(\tau, \omega) < P_b(\tau, \omega) \]  
(14)

where \( \eta_{c} \) and \( \eta_{d} \) denote the charge and discharge battery efficiency and \( \eta_{I} \) denotes the inverter efficiency.

The boundary for the energy value that can be saved in the battery bank is outlined as follows:

\[ E_b(\tau, \omega) \in \left[ n_{B}, \bar{E}_b, \underline{E}_b \right] \]  
(15)

where \( \bar{E}_b \) and \( \underline{E}_b \) are the greatest and lowest saved energy values in the battery, respectively.

The battery number within the hybrid system \((n_{B})\) is subject to the following restriction:

\[ n_{B} \in \{ 1, 2, ..., \bar{n}_{B} \} \]  
(16)

where \( \bar{n}_{B} \) is the maximum number of batteries placed in the hybrid system.

2.3.5. Inverter Model

In the hybrid system under examination, the inverter facilitates the connection of batteries to the AC bus. Considering that the greatest active load flow through the inverter is \( P_I \) [30], the number of inverters placed in the system to accommodate the batteries' maximum load flow is computed by:

\[ n_{I} = \left\lceil \frac{\max(P_B)}{P_I} \right\rceil + 1 \ \forall P_B(\tau, \omega) = E_b(\tau, \omega) - E_b(\tau - 1, \omega) \]  
(17)

where \( P_B \) is the batteries' active power.

2.4. Problem Formulation

The optimization of the hybrid system is performed to optimize the energy units and storage size to facilitate electricity and heat provision simultaneously.

Objective Function

The objective function for optimizing the hybrid system aims to minimize planning expenses, encompassing the annual installation cost \((AIC)\), annual maintenance cost \((AMC)\), annual operating cost \((AOC)\), and annual emission cost \((AEC)\).

\[ \min \ \text{Cost} = AIC + AMC + AOC + AEC \]

\[ AIC = h_{WT} n_{WT} + h_{B} n_{B} + h_{I} n_{I} + h_{C} P_{C}^{max} \]
\[ AMC = c_{WT} n_{WT} + c_{B} n_{B} + c_{I} n_{I} + c_{C} P_{C}^{max} \]
\[ AOC = FC_{C} \]
\[ AEC = EC_{C} \]  
(18)
where $h_{WT}$, $h_b$, $h_I$, $h_C$ are the AIC (USD/year) of wind turbine, battery, TES, and CHP, respectively, and $\sigma_{WT}$, $\sigma_b$, $\sigma_I$, $\sigma_C$ are AMC (USD/kW/year) of the wind turbine, battery, TES, and CHP, respectively. The $n_{WT}$, $n_b$, $n_I$, $n_T$, $P_{CCHP}$, $F_{CC}$, and $E_{CC}$ are the number of wind turbines, batteries, inverters, and TESs, the capacity of CHP, AOC (USD/year), and AEC (USD/year) of the hybrid system, respectively. In the hybrid system, only CHP has an AOC and AEC.

The AIC of each component ($\vartheta$) is determined by multiplying its overall size cost by the factor of capacity recovery for resources, storage, and inverter [15], which is presented by

$$\vartheta = \frac{\alpha(1 + \kappa)^n - 1}{\alpha}$$

where $\alpha$, $\kappa$, and $n$ are the overall capacity cost, interest rate, and life span of the device, respectively.

2.5. Stochastic Modeling with Cloud Theory

In the stochastic problem, the uncertainties surrounding the electrical and thermal demands, as well as wind speed, are taken into account. Consequently, it is recommended to employ a cloud theory-based stochastic model to address the optimization problem under these uncertainties. Cloud theory, rooted in the concept of fuzzy drops, offers a distinctive approach by representing potential values for an uncertain parameter within a specific range. Unlike other methods limited to the uncertainty of the initial event, this fuzzy-based approach adeptly handles uncertainties associated with both the first and second moments in the Probability Density Function (PDF). The cloud model (CM) theory, an innovative fusion of fuzzy logic and statistical probability, revolutionizes conventional expressions and conceptual delineations. By leveraging membership functions, this framework facilitates the assessment of uncertain measures linked with ambiguous concepts, departing from traditional fuzzy logic paradigms. Consequently, cloud theory adeptly captures the inherent vagueness and stochastic nature prevalent in both the tangible universe and individual cognition, along with their intricate interdependencies.

To elucidate the fundamental tenet of this theory, let $L$ symbolize the linguistic domain quantity $u$. The formulation for $C_L$ mapping is outlined as follows [29,34,35]:

$$C_L(x): u \to [0,1], \forall x \in u, x \to C_L(x)$$

The $C_L(x)$ within $u$ denotes the $L$ membership, serving as a standard CM when it conforms to a typical distribution pattern. The definition of each cloud relies on three essential parameters: (a) the anticipatory parameter $Ex$, (b) the entropy parameter $En$, and (c) the hyper-parameter. In Figure 2, a standard cloud model is depicted. According to this illustration, $Ex$ signifies the cloud value’s average, while $En$ represents the range of variability and disperses the cloud particles. $He$ emerges as a crucial parameter that extends the utility of cloud theory beyond that of MCS. As previously mentioned, $He$ characterizes the variability in cloud membership degrees, essentially mirroring the entropy $En$. It is noteworthy that hyper-entropy ($He$) generally adheres to a normal distribution pattern [29,34,35].
2.5.1. Production of the Normal CM

To utilize cloud theory in modeling uncertain parameters in problems, it is crucial to construct a stochastic CM for variables. This process involves three pivotal parameters essential for capturing the cloud’s characteristics: (a) the parameter of expectation $E_x$, which denotes the cloud average; (b) the parameter of entropy $E_n$, which indicates the dispersion of droplets within the cloud; and (c) the parameter of hyper-entropy $E_h$, representing the uncertainty in entropy due to randomness and fuzzy entropy. To effectively develop a cloud model, one must determine these three parameters—$E_x$, $E_n$, and $E_h$—for each random variable $x_i$. Cloud droplets ($x_i, u_i$) are formed through a series of steps based on the droplet count within the cloud. With $N$ droplets of ($x_i, u_i$), one can calculate the three distinct values $E_x$, $E_n$, and $E_h$. This paper emphasizes the computation and establishment of the primary cloud model, considering two frameworks: the normal distribution model, which is vital for uncertainty modeling related to the load, and the Weibull distribution model for wind speed. The primary phases involved in cloud production are as follows:

Phase (1): Data input: The $E_x$ value is obtained from forecast data and signifies the mean, while $E_n$ represents the standard deviation value. The $E_h$ entropy indicates the rate of spread, and $N$ refers to the droplet count.

Phase (2): Generate a random $E_n$ value that follows a normal distribution, utilizing $E_x$ and $E_h$.

Phase (3): Produce a random $x_i$ within a distribution normally based on $E_x$ and $E_n$.

Phase (4): Determine the $\mu_i$ membership degree using the following equation:

$$\mu_i = \exp\left[-\frac{(x_i - E_x)^2}{2(E_n)^2}\right]$$ (21)
Phase (5): Calculate $x_i$ and $u_i$ for all instances in $N$. To convert a small quantity into a qualitative evaluation, the regression cloud model suitable for normal distribution is utilized in the following stages.

Stage (1): Establish the mean and variance of $x_i$ as described below:

$$
\overline{X} = \frac{1}{N} \sum_{i=1}^{N} x_i, \quad S^2 = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \overline{X})^2
$$

Stage (2):

$$
Ex = \overline{X}
$$

Stage (3):

$$
En = \sqrt{\frac{\pi}{2}} \times \frac{1}{N} \sum_{i=1}^{N} |x_i - Ex|
$$

Stage (4):

$$
He = \sqrt{S^2 - En^2}
$$

2.5.2. Weibull Distribution-Based CM

The Weibull distribution is frequently applied to simulate the variability in wind turbine output. Consequently, this research incorporates this distribution into the cloud theory to demonstrate the unpredictability of wind turbine power. The process for constructing a cloud theory using the Weibull distribution is outlined as follows:

- Input data
  The Weibull function requires input data, including the parameter of shape $\beta$, the secondary shape parameter $\gamma$, the parameter of scale $\eta$, and the droplet number $N$.

- Produce Weibull-distributed values
  Generate random values distributed according to the Weibull distribution using the shape parameters $\beta$ and $\gamma$. Then, generate random numbers distributed according to the Weibull distribution with $x_i$, utilizing the parameters $\beta$ and $\gamma$.

- Certainty level calculation
  Calculate the level of certainty in the following manner $[29,34,35]$:

$$
\mu(x) = \frac{\beta'}{\beta' - 1} \times \left( \frac{\beta' - 1}{\beta'} \right)^{\frac{1}{\beta'}} \times \left( \frac{x}{\eta} \right)^{\beta'+1} \exp \left[ \frac{\beta' - 1}{\beta'} \left( \frac{x}{\eta} \right)^{\beta'} - \left( \frac{x}{\eta} \right)^{\beta'} \right]
$$

Finally, produce Weibull-distributed values and calculate the level of certainty for every $N$ droplets.

3. Proposed Meta-Heuristic Optimizer

In this research, an enhanced version of the horse herd optimizer (IHHO) is employed to tackle the intelligent stochastic optimization of the hybrid Wind/Battery/CHP/TES energy system. This section outlines the formulation of IHHO and its application in addressing the problem.

3.1. Overview of the HHO

The framework of horse herd optimization (HHO) is inspired by the daily activities of horses. It incorporates a range of behaviors observed in horses at different stages of life,
such as grazing (G), hierarchy (H), sociability (S), imitation (I), defense structure (D), and roaming (R) [36].

The description of how horses move in each cycle is outlined in [36].

\[ X_{m}^{\text{Iter,AGE}} = V_{m}^{\text{Iter,AGE}} + X_{m}^{(\text{Iter-1),AGE}}, \text{AGE} = \alpha, \beta, \gamma, \delta \]  

(27)

In this equation, \( X_{m}^{\text{Iter,AGE}} \) represents the horse’s location \( m \) at iteration \( \text{Iter} \), \( X_{m}^{(\text{Iter-1),AGE}} \) denotes the horse’s location \( m \) at iteration \( \text{Iter-1} \), \( \text{AGE} \) signifies the age range of the horse, and \( \text{Iter} \) represents the present iteration. Additionally, \( V_{m}^{\text{Iter,AGE}} \) represents the horse speed vector. The age ranges are categorized as follows: \( \delta \) for horses aged between \( 0 \) and \( 5 \) years, \( \gamma \) for those aged between \( 5 \) and \( 10 \) years, \( \beta \) for horses aged between \( 10 \) and \( 15 \) years, and \( \alpha \) for horses older than \( 15 \) years. Within the response matrix used in HHO, the first \( 10\% \) corresponds to horses categorized as \( \alpha \), the next \( 20\% \) corresponds to \( \beta \), and the remaining \( 70\% \) is divided between \( \gamma \) and \( \delta \) [36].

The vector representing the horses’ movement across several age groups during every algorithm iteration is described in detail by [36]

\[ V_{m}^{\text{Iter,a}} = \bar{V}_{m}^{\text{Iter,a}} = Z_{m}^{\text{Iter,a}} + D_{m} \]  

(28)

\[ V_{m}^{\text{Iter,b}} = \bar{V}_{m}^{\text{Iter,b}} = Z_{m}^{\text{Iter,b}} + H_{m}^{\text{Iter,b}} + S_{m}^{\text{Iter,b}} \]  

(29)

\[ V_{m}^{\text{Iter,y}} = \bar{V}_{m}^{\text{Iter,y}} + S_{m}^{\text{Iter,y}} + I_{m}^{\text{Iter,y}} + \bar{D}_{m}^{\text{Iter,y}} \]  

(30)

\[ V_{m}^{\text{Iter,\delta}} = \bar{V}_{m}^{\text{Iter,\delta}} + I_{m}^{\text{Iter,\delta}} + \bar{R}_{m}^{\text{Iter,\delta}} \]  

(31)

Below, detailed descriptions of lifelong behavioral patterns demonstrated by horses are provided.

**Grazing (G):** By employing a factor denoted as \( g \), the grazing area surrounding each horse is simulated. Horses are allowed to graze continuously throughout their life spans. The definition of equine grazing behavior is presented below [36]:

\[ g_{m}^{\text{Iter,AGE}} = g_{m}^{\text{Iter}} \left( \bar{u} + p \bar{l} \right) \times \left| X_{m}^{(\text{Iter-1})} \right|, \text{AGE} = \alpha, \beta, \gamma, \delta \]  

(32)

\[ g_{m}^{\text{Iter,AGE}} = g_{m}^{(\text{Iter-1),AGE}} \times W_{g} \]  

(33)

where the moving parameter of horse \( i \) is represented by \( \bar{V}_{m}^{\text{Iter,AGE}} \), which decreases with each iteration corresponding to \( \omega_{i} \) in a linear manner. \( \bar{l} \) and \( \bar{u} \) denote the lowest and greatest limits of the grazing area, respectively, ranging between \( 0.95 \) and \( 1.05 \). \( p \) represents a number between \( 0 \) and \( 1 \), and \( g \) is set to \( 1.5 \) for all horses, irrespective of their age [36].

**Hierarchy (H):** The horses are predominantly overseen by a leader who directs human activities. Furthermore, both male and female horses can lead a herd of wild horses. The horses’ herd inclination for following the strongest and most knowledgeable leader is represented by the coefficient \( h \). The depiction of this sequential behavior is outlined as follows [36]:

\[ \bar{H}_{m}^{\text{Iter,AGE}} = h_{m}^{\text{Iter,AGE}} \times \bar{V}_{m}^{\text{Iter-1),AGE}} \times \left| X_{m}^{(\text{Iter-1})} \right|, \text{AGE} = \alpha, \beta, \gamma \]  

(34)

\[ h_{m}^{\text{Iter,AGE}} = h_{m}^{(\text{Iter-1),AGE}} \times W_{h} \]  

(35)

where \( \bar{H}_{m}^{\text{Iter,AGE}} \) represents the influence of the best horse position in terms of speed, and \( X_{m}^{(\text{Iter-1})} \) indicates the optimal horse position.

**Sociability (S):** Horses maintain a social environment to secure their survival and welfare. Their social behavior is indicated by the parameter \( s \), which is evident in their inclination to approach the positions of other horses. Most horses, categorized as \( \beta \) and \( \gamma \), prioritize herd life, as explained below [36].
\[ S_{\text{Iter,AGE}} = S_{\text{Iter,AGE}} \left[ \frac{1}{N} \sum_{j=1}^{N} \hat{X}_j^{(\text{iter-1})} \right], AGE = \beta, \gamma \] (36)

\[ S_{\text{Iter,AGE}} = S_{\text{Iter,AGE}}^{(\text{iter-1}),AGE} \times w_s \] (37)

where \( S_{\text{Iter,AGE}} \) represents the movement vector of horse \( i \), while \( S_{\text{Iter,AGE}}^{(\text{iter-1}),AGE} \) denotes the movement direction of horse \( i \) concerning the livestock during the iteration. Taking into account the coefficient \( \omega_n \), the value of \( S_{\text{Iter,AGE}} \) diminishes with each iteration. \( AGE \) signifies the age of each horse, and \( N \) represents the total number of horses.

**Imitation:** The illustration in Figure 3 depicts the imitation behavior of horses, where they mimic each other’s actions such as locating appropriate grazing land. The degree of imitation among horses is assessed by a factor denoted as \( i \). This habit is more pronounced in younger horses [36].

\[ \hat{I}_{\text{Iter,AGE}} = \hat{i}_{\text{Iter,AGE}} \left[ \frac{1}{pN} \sum_{j=1}^{N} \hat{X}_j^{(\text{iter-1})} \right], AGE = \gamma \] (38)

\[ \hat{i}_{\text{Iter,AGE}} = \hat{i}_{\text{Iter,AGE}}^{(\text{iter-1}),AGE} \times w_i \] (39)

where \( \hat{I}_{\text{Iter,AGE}} \) is the movement of the horse \( i \) vector with respect to a horse at positions \( \hat{x} \), and \( pN \) represents the percentage of horses that achieved the highest positions.

![Figure 3. The mimicking conduct displayed by the horses.](image)

**Defense mechanism (D):** The horses display protective actions, which involve fleeing from threats and yielding, considered as less effective responses. These protective actions are characterized by the factor \( d \). In the following model, the horses’ defensive conduct is indicated by a negative factor, aiming to discourage them from unfavorable outcomes [36].

\[ \hat{D}_{\text{Iter,AGE}} = -d_{\text{Iter,AGE}} \left[ \frac{1}{qN} \sum_{j=1}^{N} \hat{X}_j^{(\text{iter-1})} \right], AGE = \alpha, \beta, \gamma \] (40)

\[ d_{\text{Iter,AGE}} = d_{\text{Iter,AGE}}^{(\text{iter-1}),AGE} \times w_d \] (41)

where \( w_d \) represents the reduction rate per iteration, \( qN \) is the count of horses with the least favorable positions, and \( \hat{D}_{\text{Iter,AGE}} \) denotes the vector of horse \( i \) escape.

**Roaming:** In their natural habitat, horses roam and shift between grasslands and pastures in search of food. The coefficient \( r \) defines the erratic movements associated with this
wandering behavior, which is more common among young horses and tends to diminish as they grow older. The definition of the roaming habit is delineated by

\[ \mathbf{R}_{\text{Iter,AGE}} = r_{\text{Iter,AGE}} pX_{\text{iter}}^{(\text{iter}-1)}, \text{AGE} = \gamma, \delta \]  

(42)

\[ r_{\text{Iter,AGE}} = r_{\text{iter}}^{(\text{iter}-1)} \times w_p \]  

(43)

where \( \mathbf{R}_{\text{Iter,AGE}} \) denotes the speed vector of horse \( i \) utilized for random escape from local minima, while \( \omega_p \) indicates the decrease in a constant per iteration.

The pseudocode for HHO is depicted in Algorithm 1.

**Algorithm 1: Horse herd optimization**

(a) Fundamental framework: Setting up the algorithm’s parameters and variables.
(b) Initial placement: Randomly dispersing horses across the search space.
(c) Evaluating fitness: Assessing the fitness level of each horse based on its location.
(d) Age determination: Calculating the age of each horse (\( \alpha, \beta, \gamma, \delta \)).
(e) Velocity adjustment: Adjusting the velocity of each horse relative to its age.
(f) Updating positions: Modifying the search space to accommodate the new positions of each horse.
(g) Convergence check: Returning to step c until the algorithm terminates and the convergence criterion is met.

3.2. Overview of the IHHO

The existing body of research indicates that conventional algorithms encounter difficulties when seeking optimal solutions in complex problem scenarios or when dealing with combined approaches, often becoming trapped in local optima. To mitigate these challenges, specific integration techniques have been proposed as a partial remedy. In this study, the RDR is employed to address premature convergence issues encountered by the traditional HHO. The HHO is prone to becoming ensnared in local minima and prematurely converging due to the complexity of the problem and the combined structures involved. To enhance the traditional HHO’s performance in the face of these challenges, the RDR [37] is applied, resulting in the development of the improved HHO (IHHO). In this approach, the RDR local search technique’s starting search direction serves as the coordinate axes, which rotate in these directions prior to transitioning to a fresh starting place where productive actions are produced.

This procedure keeps going until, in any search orientation, preferably one effective phase and one failure step are found. The present phase ends at this point, and the recognition foundation is looked at to determine the total effect of every stage that was effective in all dimensions [37]. The subsequent protocol is used to update the orthonormal foundation:

\[ x^{k+1} - x^{k+} = \sum_{i=1}^{n} \lambda_i d_i \]  

(44)

The equation below outlines a series of directives. Here, \( \lambda_i \) denotes the aggregate count of successful variables, while \( x^{k+1} - x^{k+} \) indicates the point exhibiting the most beneficial search trajectory. Consequently, it is integrated into the adjusted search orientation.

\[ p_i = \begin{cases} 
  d_i \lambda_i = 0 & \quad \lambda_i \neq 0 \\
  \sum_{j=0}^{n} \lambda_j d_j \lambda_i \neq 0 
\end{cases} \]  

(45)

Subsequently, the outcomes of the search, following the Gram–Schmidt normalizing process, are revised according to the subsequent equation.
\[ q_i^t = \begin{cases} p_i, & i = 1 \\ p_i - \sum_{j=1}^{i-1} q_j^t - p_i, & i \geq 2 \end{cases} \]  

(46)

The revised and standardized search instructions are outlined by

\[ d_i = \frac{q_i}{||q_i||}, i = 1, 2, 3, \ldots, n. \]  

(47)

Following the local search adjustment, this approach conducts the search procedure until the algorithm fulfills the convergence criteria in the new opposing direction. The IHHO Flowchart is depicted in Figure 4.

![Image of a flowchart showing the IHHO algorithm steps](https://via.placeholder.com/150)

**Figure 4.** The IHHO Flowchart.
3.3. The IHHO Implementation

Expanding on the conceptual overview given, we can outline the procedural steps of the IHHO algorithm for solving deterministic optimization problems:

1. **Initialization**: The algorithm starts by generating an initial population of horses within the search space in a random manner. Every horse symbolizes a potential solution to the optimization problem.

2. **Fitness Evaluation**: Each horse’s fitness is assessed by utilizing the objective function of the optimization problem. The candidate solutions’ quality is evident in this.

3. **Herd Movement**: The horses in the herd exhibit movements that mimic the natural behavior of horses. This involves horses taking the lead in guiding the herd, other horses following and aligning themselves with the herd’s direction, and some horses lagging behind to explore new regions of the search space.

4. **The IHHO incorporates a technique called RDR local search to address the problem of premature convergence. This process entails rotating the coordinate axes in the direction of the initial search direction and subsequently transitioning to a new starting point to generate effective search actions.**

5. **Orthonormal Basis Update**: Utilizing the equations provided in the overview, the orthonormal basis is updated following the RDR local search. This allows for the ongoing enhancement and optimization of the search directions.

6. **Convergence check**: The algorithm assesses if the termination criteria, such as a maximum number of iterations or a target fitness value, have been met. Otherwise, the process goes back to Step 3 for the next iteration.

7. **Output**: Upon convergence, the IHHO outputs the most optimal solution discovered, which represents the best or second-best solution to the deterministic optimization problem.

By incorporating the RDR local search into the HHO framework and consistently updating the orthonormal basis, the IHHO demonstrates strong problem-solving capabilities and effectively prevents premature failure. This modification of the original HHO algorithm is anticipated to result in enhanced optimization performance for various deterministic optimization problems.

4. Results and Discussion

4.1. Application and Simulation Scenarios

The proposed methodology is used for the hybrid Wind/Battery/CHP/TES system depicted in Figure 1, utilizing real data obtained from the city of Al-Jubail (26.9598° N, 49.5687° E) in Saudi Arabia. This system is characterized by electrical and thermal demand peaks of 15 kW and 5 kW, respectively. The load profiles for both electrical and thermal consumers hourly and daily, derived from peak load and demand curve data, are illustrated in Figure 5 [15]. The maximum wind speed in the specified area is recorded at 15 m/s. Figure 6 illustrates the daily load curve [15]. Furthermore, Table 1 provides the techno-economic data concerning resources and storage.

<table>
<thead>
<tr>
<th>Resource</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>WT</td>
<td>(p_r) (kW)</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>(v_{\text{c}}) (m/s)</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>(v_r) (m/s)</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>(v_{\text{c}}) (m/s)</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>Peak wind speed (m/s)</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>(\bar{\pi}_{\text{WT}})</td>
<td>35</td>
</tr>
<tr>
<td></td>
<td>(\alpha_{\text{WT}}) (USD)</td>
<td>3200</td>
</tr>
<tr>
<td>Component</td>
<td>Parameter</td>
<td>Value</td>
</tr>
<tr>
<td>-----------</td>
<td>-----------</td>
<td>-------</td>
</tr>
<tr>
<td>WT</td>
<td>( \sigma_{W} ) (USD/year)</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>Life span (year)</td>
<td>20</td>
</tr>
<tr>
<td>CHP</td>
<td>( \eta_I ) (%)</td>
<td>38</td>
</tr>
<tr>
<td></td>
<td>( \eta_M ) (%)</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>( \eta_T ) (%)</td>
<td>38</td>
</tr>
<tr>
<td></td>
<td>( \sigma_P ) (USD/kg)</td>
<td>0.0037</td>
</tr>
<tr>
<td></td>
<td>( f_P ) (USD/l)</td>
<td>1.24</td>
</tr>
<tr>
<td></td>
<td>( \chi_c ) (l/kWh)</td>
<td>0.246</td>
</tr>
<tr>
<td></td>
<td>( \gamma_c ) (l/kWh)</td>
<td>0.0845</td>
</tr>
<tr>
<td></td>
<td>( \beta_c ) (kg/kW)</td>
<td>3.25</td>
</tr>
<tr>
<td></td>
<td>( P_c ) (kW)</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>( \alpha_c ) (USD/kW)</td>
<td>901.65</td>
</tr>
<tr>
<td></td>
<td>( \sigma_c ) (USD/kW/year)</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>Life span (year)</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>( \kappa ) (%)</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>CF (%)</td>
<td>70</td>
</tr>
<tr>
<td>Battery</td>
<td>( \bar{E}_g ) (kWh)</td>
<td>1.35</td>
</tr>
<tr>
<td></td>
<td>( E_g ) (kWh)</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>( \eta_I / \eta_T ) (%)</td>
<td>90</td>
</tr>
<tr>
<td></td>
<td>( \sigma )</td>
<td>0.0002</td>
</tr>
<tr>
<td></td>
<td>( \bar{x} )</td>
<td>90</td>
</tr>
<tr>
<td></td>
<td>( \alpha_B ) (USD)</td>
<td>130</td>
</tr>
<tr>
<td></td>
<td>( \sigma_B ) (USD/year)</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Life span (year)</td>
<td>5</td>
</tr>
<tr>
<td>Inverter</td>
<td>( P_I ) (kW)</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>( \eta_I ) (%)</td>
<td>95</td>
</tr>
<tr>
<td></td>
<td>( \alpha_I ) (USD)</td>
<td>2000</td>
</tr>
<tr>
<td></td>
<td>( \sigma_I ) (USD/year)</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Life span (year)</td>
<td>10</td>
</tr>
<tr>
<td>TES</td>
<td>( \bar{E}_T ) (kWh)</td>
<td>1.5</td>
</tr>
<tr>
<td></td>
<td>( E_T ) (kWh)</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>( \eta_I / \eta_T ) (%)</td>
<td>78</td>
</tr>
<tr>
<td></td>
<td>( \sigma )</td>
<td>0.0002</td>
</tr>
<tr>
<td></td>
<td>( \bar{x} )</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>( \alpha_T ) (USD)</td>
<td>210</td>
</tr>
<tr>
<td></td>
<td>( \sigma_T ) (USD/year)</td>
<td>1.6</td>
</tr>
<tr>
<td></td>
<td>Life span (year)</td>
<td>10</td>
</tr>
</tbody>
</table>
The simulations were implemented in Matlab 2021b and independent runs were executed on a desktop PC with an Intel Core i5-4590M processor @ 3.30 GHz, 8GB RAM, under the Windows 7 64-bit OS. The parameters for the population size, maximum iteration, and independent runs are set to 50, 300, and 30, respectively, for both the IHHO and comparative algorithms such as HHO, PSO, and MRFO, as detailed in [36,42,43]. Simulation scenarios assessing the effectiveness of the methodology are outlined as follows:

- Scenario 1: Optimization of the hybrid Wind/Battery system;
- Scenario 2: Optimization of the hybrid Wind/CHP/Battery system;
- Scenario 3: Optimization of the hybrid Wind/CHP/Battery/TES system.

4.2. Deterministic Results of Scenario 1

In this section, the outcomes of the deterministic optimization process for scenario 1, focusing on the hybrid Wind/Battery energy system, are presented. Table 2 illustrates the
capacities of various sources and storage units. The results indicate that in scenario 1, which solely accounts for WT and batteries, approximately 22 wind turbines and 108 batteries are necessary to meet the electrical demand requirements over a 24 h period. Six inverters are required to install this battery quantity to the AC bus. The thermal demand and supply are not incorporated in this instance. As depicted in Table 3, the calculated costs for AIC and AMC amount to USD 7528 and USD 110, respectively, with no expenses for AOC and AEC in scenario 1. Consequently, the total system cost using the IHHO is determined to be USD 7638 in scenario 1.

Table 2. Sizing results of resources and storage in scenario 1.

<table>
<thead>
<tr>
<th>Device</th>
<th>Number/Value</th>
<th>Cost (USD/year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind Turbine</td>
<td>22</td>
<td>7638</td>
</tr>
<tr>
<td>Battery</td>
<td>108</td>
<td></td>
</tr>
<tr>
<td>Inverter</td>
<td>6</td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Cost components of resources and storage in scenario 1.

<table>
<thead>
<tr>
<th>AIC (USD/year)</th>
<th>AMC (USD/year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind turbine</td>
<td>Battery</td>
</tr>
<tr>
<td>3520</td>
<td>2808</td>
</tr>
</tbody>
</table>

AOC (USD/year) | AEC (USD/year) |
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind turbine</td>
<td>Battery</td>
</tr>
<tr>
<td>Without cost</td>
<td>-</td>
</tr>
</tbody>
</table>

Figure 7 depicts the performance of WT and batteries in supplying the electrical load in scenario 1. As observed, the anticipated daily power curve of WT exhibits fluctuations, mirroring the variations in wind speed indicated in Figure 6. Further examination of Figure 7 reveals that WT generate surplus active power compared to the AC power demand during the time intervals from 1:00 to 10:00 and 19:00 to 24:00. Consequently, the extra energy generated by WT during these hours relative to the electrical load is stored in batteries. During these intervals, as depicted in Figure 7, batteries are in a charging state, resulting in negative active power values. Simultaneously, the batteries switch to a mode of discharge to compensate for the insufficient energy generated using wind units in contrast to the electrical demand.

Figure 7. Contribution of generation, storage units, and electrical demand over 24 h in scenario 1.
4.3. Deterministic Results of Scenario 2

In this section, the outcomes of deterministic optimization for the hybrid Wind/CHP/Battery system are presented. Scenario 2, outlined in Table 4, demonstrates a reduction in the wind units, batteries, and inverters to nine, 65, and three, respectively, compared to scenario 1, respectively. Despite this reduction, both electrical and thermal loads are concurrently supplied. Achieving this balance entails the installation of a single 8.77 kW CHP unit. As indicated in Table 5, the costs of AIC and AMC amount to USD 4125.39 and USD 80.08, respectively, while the costs of AOC and AEC stand at USD 2111.28 and USD 539.84, respectively, for scenario 2. Consequently, the overall system planning cost is USD 6856.59 in scenario 2, as determined by the IHHO.

Table 4. Sizing results of resources and storage in scenario 2.

<table>
<thead>
<tr>
<th>Device</th>
<th>Wind Turbine</th>
<th>Battery</th>
<th>Inverter</th>
<th>CHP Capacity (kW)</th>
<th>Cost (USD/Year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number/Value</td>
<td>9</td>
<td>65</td>
<td>3</td>
<td>8.77</td>
<td>6856.59</td>
</tr>
</tbody>
</table>

Table 5. Cost components of resources and storage in scenario 2.

<table>
<thead>
<tr>
<th>Device</th>
<th>Wind Turbine</th>
<th>Battery</th>
<th>Inverter</th>
<th>TES</th>
<th>CHP</th>
<th>AIC</th>
<th>WT</th>
<th>Battery</th>
<th>Inverter</th>
<th>TES</th>
<th>CHP</th>
<th>AMC</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIC (USD/year)</td>
<td>1440</td>
<td>1690</td>
<td>600</td>
<td>-</td>
<td>395.39</td>
<td>4125.39</td>
<td>45</td>
<td>0</td>
<td>0</td>
<td>-</td>
<td>35.08</td>
<td>80.08</td>
</tr>
<tr>
<td>AOC (USD/year)</td>
<td>Without cost</td>
<td>2111.28</td>
<td>2111.28</td>
<td>Without cost</td>
<td>539.84</td>
<td>539.84</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 8 illustrates the anticipated daily trends of the generated power by wind units and batteries, alongside the CHP electrical and heat power, while meeting both demands in scenario 2. As depicted in Figure 8, although the wind unit power changes during a day remain consistent with those of scenario 1, numerical differences are evident between the two scenarios. In scenario 2, the active power of WTs is consistently lower than the electrical load throughout all operational hours. Additionally, Figure 9 showcases that the CHP heat power matches the thermal load throughout the entire operational duration, reflecting the assumption in scenario 2 that the CHP is only available to supply the heat demand. Consequently, the anticipated changes for the CHP production in Figure 8 mirror those of CHP thermal power (Figure 9), differing only in numerical values. Consequently, during the hours of 1:00–10:00 and 19:00–24:00, the combined CHP and wind unit active power exceeds the electrical load, prompting the batteries to enter charging mode and save surplus energy generated by these units relative to the electrical load. Conversely, during other times, storage-based batteries operate in discharge mode and, with wind turbines and CHPs, provide the electrical load requirements.
4.4. Deterministic Results of Scenario 3

In this section, the deterministic optimization outcomes of the Wind/CHP/Battery/TES system are delineated for scenario 3. In this scenario, the quantities of wind turbines, batteries, and inverters are determined as eight, 64, and four, respectively (as listed in Table 6). Additionally, five TESs are incorporated into the proposed system, resulting in a reduction in CHP capacity to 8.42 kW compared to scenario 2. As outlined in Table 7, the costs pertaining to AIC, AMC, AOC, and AEC amount to USD 4176.61, USD 81.68, USD 2008.87, and USD 510.45, respectively, for scenario 3. Consequently, the overall system cost is calculated as USD 6777.61 in scenario 3 utilizing the IHHO.

Figure 10 depicts the anticipated power profiles of production and storage resources when fulfilling the electrical and thermal demands in scenario 3. According to Figure 10, the WT power variations remain consistent with scenario 2, failing to fully meet the electrical load requirement throughout the study period. In Figure 9, the CHPs consistently produce 1.5 kW of heat power across maximum operating hours, exceeding the thermal load demand between 1:00–6:00 and 15:00–24:00. Consequently, TESs operate in charging mode during these intervals, accumulating surplus heat energy generated using the CHPs.
beyond the thermal demand. However, during other periods, when the CHPs cannot entirely fulfill the heat demand, the TESs switch to the mode of discharge, compensating for the shortfall in thermal energy production in contrast to the CHP. Evaluating Figures 10 and 11, it is evident that in scenario 3, the inclusion of TESs allows for better control over CHP thermal power. The presence of TESs in scenario 3 enables a reduction in CHP size compared to scenario 2, as corroborated by Table 7. Ultimately, the operational act of CHPs and wind turbines results in extra power relative to the electrical demand during the hours of 1:00–10:00 am and 10:00–12:00 pm, necessitating the batteries to operate in charging mode. Conversely, during the remaining hours, the storage-based battery, CHPs, and wind turbines fulfill the electrical demand.

Figure 10. Contribution of resources, storage units, and electrical demand over 24 h in scenario 3.

Table 6. Sizing results of resources and storage in scenario 3.

<table>
<thead>
<tr>
<th>Device</th>
<th>Wind Turbine</th>
<th>Battery</th>
<th>Inverter</th>
<th>CHP Capacity (kW)</th>
<th>TES</th>
<th>Cost (USD/Year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number/Value</td>
<td>8</td>
<td>62</td>
<td>4</td>
<td>8.42</td>
<td>5</td>
<td>6777.61</td>
</tr>
</tbody>
</table>

Table 7. Cost components of resources and storage in scenario 3.

<table>
<thead>
<tr>
<th>Wind Turbine</th>
<th>Battery</th>
<th>Inverter</th>
<th>TES</th>
<th>CHP</th>
<th>AIC (USD/year)</th>
<th>AMC (USD/year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1280</td>
<td>1612</td>
<td>800</td>
<td>105</td>
<td>379.61</td>
<td>2008.87</td>
<td>2008.87</td>
</tr>
<tr>
<td>AOC (USD/year)</td>
<td>AEC (USD/year)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wind Turbine</td>
<td>Battery</td>
<td>Inverter</td>
<td>TES</td>
<td>CHP</td>
<td>AOC (USD/year)</td>
<td>WT</td>
</tr>
<tr>
<td>1280</td>
<td>1612</td>
<td>800</td>
<td>105</td>
<td>379.61</td>
<td>2008.87</td>
<td>2008.87</td>
</tr>
</tbody>
</table>
4.5. Comparison of the Deterministic Results

Table 8 presents a comparative analysis of the planning costs across different scenarios using the IHHO, indicating that scenario 3 has the lowest planning costs compared to the other scenarios. As per Table 3, scenario 1 incurs the highest installation and maintenance costs, amounting to USD 7528 and USD 110, respectively. Scenario 2, which involves the installation of CHP alongside WTs and batteries, experiences a reduction in costs of investment and maintenance in contrast to scenario 1, totaling USD 4125.39 and USD 80.08, respectively. The reduction in cost in scenario 2 is attributed to the decreased number of wind turbines, batteries, and inverters compared to scenario 1. However, scenario 2 incurs operating and emission costs of USD 211.28 and USD 539.84, respectively, due to the fuel cost associated with CHP. In scenario 3, where TES is integrated with CHP, wind turbines, and batteries, costs of operation and emission decrease in contrast to scenario 2, amounting to USD 2008.87 and USD 510.45, respectively. The reduction in the cost in scenario 3 is attributed to the contributions of CHP and TES. However, installation and maintenance costs in scenario 3 increase compared to scenario 2 (USD 4125.39 and USD 80.08), totaling USD 4176.61 and USD 81.68, respectively. This cost increase in scenario 3 is due to the installation of five TESs, incurring installation and maintenance/repair costs of USD 105 and USD 8, respectively. Consequently, in scenario 3, the installation and maintenance costs of CHP decrease by 4% compared to scenario 2.

Table 8. Comparison of the planning cost for different scenarios using the IHHO.

<table>
<thead>
<tr>
<th>Scenario/Item</th>
<th>Cost (USD/Year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>7638.00</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>6856.59</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>6646.61</td>
</tr>
</tbody>
</table>

4.6. Proposed Optimizer Superiority

Figure 12 depicts the convergence curves of various optimizers in solving the optimal scenario, specifically scenario 3. Table 6 compares the convergence process of the recommended IHHO with HHO, PSO, and MRFO methods. The parameters for each algorithm, such as the size of the population, maximum iterations, and independent executions, are
set as 50, 300, and 30, respectively. Algorithm adjustment parameters are determined based on previous references. Each optimizer is performed 30 times to derive statistical analysis results, including the best, average, and worst values, along with the standard deviation (Std) of the optimal solution. As shown in Table 9, the improved optimizer achieves the answer optimally corresponding to the lowest objective function value compared to other algorithms. The IHHO achieves this cost value with the greatest convergence speed, requiring fewer iterations and less computation time. Additionally, the Std obtained for the improved algorithm is the lowest compared to other algorithms. Consequently, the improved algorithm offers a more precise solution and faster convergence speed than the HHO, PSO, and MRFO.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Best Cost (USD)</th>
<th>Mean Cost (USD)</th>
<th>Worst Cost (USD)</th>
<th>Std (USD)</th>
<th>CT (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IHHO</td>
<td>6646.61</td>
<td>6664.03</td>
<td>6675.11</td>
<td>146.32</td>
<td>115</td>
</tr>
<tr>
<td>HHO</td>
<td>6655.04</td>
<td>6676.04</td>
<td>6690.04</td>
<td>309.33</td>
<td>144</td>
</tr>
<tr>
<td>PSO</td>
<td>6652.32</td>
<td>6672.61</td>
<td>6684.36</td>
<td>247.59</td>
<td>138</td>
</tr>
<tr>
<td>MRFO</td>
<td>6673.27</td>
<td>6688.54</td>
<td>6705.02</td>
<td>366.15</td>
<td>149</td>
</tr>
</tbody>
</table>

Figure 12. Convergence process of different optimizers solving scenario 3.

4.7. Stochastic Model Results

The system’s optimization efficacy has been assessed under uncertain load and wind power conditions utilizing the cloud theory model and the IHHO approach. To enact the stochastic optimization model, 1000 droplets have been chosen to construct cloud models for electric and thermal demands, as well as wind speed. The parameters of cloud loading and wind speed CM are detailed in Table 10. Figure 13 shows the cloud droplet distribution pattern for wind speed and electrical and thermal loads.
Table 10. CM parameters of wind, and electrical and thermal load.

<table>
<thead>
<tr>
<th>CM Parameter</th>
<th>Demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E_x$</td>
<td>Base State</td>
</tr>
<tr>
<td>$E_n$</td>
<td>10% $E_x$</td>
</tr>
<tr>
<td>$H_e$</td>
<td>10% $E_n$</td>
</tr>
<tr>
<td>$\beta$</td>
<td>5</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>20</td>
</tr>
</tbody>
</table>

Tables 11 and 12 provide the outcomes of system optimization under stochastic conditions, employing the cloud theory model and the IHHO technique. These tables outline the values of $E_x$, $E_n$, and $H_e$, alongside the planning costs for various scenarios. The findings indicate that incorporating uncertainty into stochastic optimization results in a higher cost of planning in contrast to the deterministic model. This escalation in costs for scenarios 1 to 3 amounts to 4.00%, 4.20%, and 3.96%, respectively, attributed to the uncertainty surrounding wind power and loads. Consequently, in the stochastic model, wind turbine power production may fall short of predicted values in deterministic optimization, and load power consumption might exceed predicted values under uncertain conditions.

![CM droplet distribution](image)

Figure 13. CM droplet distribution for wind speed (a), electrical loading (b), and thermal loading (c).

Table 11. Values of $E_x$, $E_n$, and $H_e$ for the stochastic optimization.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E_x$</td>
<td>7944</td>
<td>7145.15</td>
</tr>
<tr>
<td>$E_n$</td>
<td>64.11</td>
<td>57.67</td>
</tr>
<tr>
<td>$H_e$</td>
<td>12.6</td>
<td>11.33</td>
</tr>
</tbody>
</table>
Table 12. Comparison of the deterministic and stochastic optimization results.

<table>
<thead>
<tr>
<th>Scenario/Item</th>
<th>Cost (USD/Year)</th>
<th>The Cost Increase Percentage Due to Uncertainties (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>Deterministic: 7638.00</td>
<td>Stochastic: 7944.00</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>Deterministic: 6856.59</td>
<td>Stochastic: 7145.15</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>Deterministic: 6646.61</td>
<td>Stochastic: 6910.48</td>
</tr>
</tbody>
</table>

Figure 14 depicts the distribution of cloud droplets, representing the planning cost across various scenarios. Observing these figures, it is evident that the fluctuations in cloud droplets on the right side of the cloud models are comparatively smaller than those on the left side, primarily due to uncertainty. Consequently, the impact of uncertainty on cost manifests as a gradual rise in cost entropy, with higher uncertainty levels resulting in more significant cost increments.

5. Conclusions

This study demonstrated the random improvement of a wind, battery, CHP, and TES system using the IHHO algorithm and cloud model theory. The primary objective was to minimize planning expenditures while fulfilling both thermal and electrical load requirements. The methodology involved a comprehensive system description, precise component modeling, problem formulation, and the application of cloud theory to handle uncertainties through stochastic modeling. We utilized the IHHO algorithm, which incorporates the RDR method, to overcome the limitations of the conventional HHO.

We validated the proposed methodology by optimizing three distinct configurations of hybrid energy systems using real-world data from Al-Jubail, Saudi Arabia. The results indicated that the configuration integrating wind, CHP, batteries, and TES achieved the lowest planning cost, with notable reductions in both investment and maintenance expenses. This underscores the significant role of thermal energy storage in enhancing the cost-effectiveness of hybrid energy systems.

Furthermore, the IHHO algorithm demonstrated superior performance in terms of convergence speed and accuracy compared to HHO, PSO, and MRFO. We attribute this
improvement to its enhanced capability to efficiently locate optimal solutions while avoiding premature convergence. However, the stochastic optimization based on the cloud model resulted in an increase in annual planning costs relative to deterministic optimization, ranging from 4.00% to 4.20%. This increase highlights the impact of uncertainties in wind power generation and demand, underscoring the necessity of incorporating stochastic modeling in the optimization process.

Future research will concentrate on the robust optimization of hybrid energy systems, including wind/CHP/hydrogen/TES configurations, with a focus on uncertainty risk aversion. Such advancements will further enhance the reliability and cost-effectiveness of sustainable energy systems for managing unpredictable variables.

**Funding:** This research is supported by the Deputyship for Research & Innovation, Ministry of Education in Saudi Arabia under Project Number (IFP-2020-162).

**Institutional Review Board Statement:** Not applicable.

**Data Availability Statement:** The data presented in this study are available in this article.

**Conflicts of Interest:** The authors declare no conflicts of interest.

**References**


Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.