FACTA UNIVERSITATIS
Series: **Electronics and Energetics** Vol. 39, Nº 1, March 2026, pp. 149 - 179
https://doi.org/10.2298/FUEE2601149C

Original scientific paper

CRISCROSS OPTIMIZATION (CCO)-BASED OPTIMAL DISPATCH STARTEGY FOR INTEGRATED HYDRO-THERMAL-WIND SCHEDULING

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Abstract. *Incorporating renewable energy resources (RER) into standard power flow schedules is a complex optimization issue with multiple objectives and nonlinear characteristics. This matter necessitates the careful assessment of a multitude of economic and environmental concerns. This matter requires the evaluation of many restrictions related to disparities between races. The primary goal of generation scheduling is to minimize pollution emissions and costs over a limited time frame. This must be accomplished while ensuring that all system restrictions are adhered to. The Crisscross optimization (CCO) algorithm is used in this research to provide a novel method for solving the short-term hydro-thermal power scheduling (ST-HTPS) and short-term hydro-thermal-wind power scheduling (ST-HTWPS) issues. The suggested CCO method is compared to previously implemented particle swarm optimization (PSO) algorithms, moth-flame optimization (MFO) algorithms, and genetic algorithms (GA). This strategy makes convergence happen faster and solutions more precise while retaining a balance between exploration and exploitation. The proposed model takes into account real-time operational limitations, such as water balance equations, ramp rate limits, and wind uncertainty, to make sure that scheduling is both practical and effective. The suggested systems serve as study examples to evaluate the actual enhancement of the proposed CCO compared to PSO, MFO, PSO, and GA. The simulation outcomes indicate that the recommended CCO modeling offers a more advantageous option than previous heuristic techniques regarding financial considerations (36389.25 \$/day) and reduced emissions (9436.29 lb/day). Despite considering the inclusion of several intricate constraints related to ST-HTWPS scenarios, these findings remain unaltered.*

Key words: *Hydro-thermal-wind scheduling, renewable energy, non-linear constraints, optimization, Crisscross optimization (CCO)*

Received May 05, 2025; revised July 25, 2025, and August 22, 2025; accepted August 29, 2025
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Nomenclature

i, j, k : The relative indexes for thermal, hydro, and wind power units

C_T, F_T, W_T : *Total expense, fuel expense, and wind expense, in that order*

N_t, N_h, N_w : *Quantity of all thermal, hydro, and wind units combined*

τ, T : *Time sub-interval and Scheduling period, respectively*

Up : *The reservoir's upstream index*

$Q_{hj,\tau}, I_{hj,\tau}$: *Rate of intake and discharge of the j^{th} hydro unit, respectively*

$P_{ti,\tau}, P_{hj,\tau}, P_{wk,\tau}$: *Thermal, hydro, and wind of i^{th}, $j^{th,}$ and k^{th} at τ*

$V_{hj,\tau}, S_{hj,\tau}$: *Reservoir volume and spillage of j^{th} hydro unit τ respectively*

$P_{d,\tau}, P_{L,\tau}$: *Total demand and transmission loss at τ*

$OEC_{wk,\tau}, UEC_{wk,\tau}$: *Over and underestimation cost of k^{th} wind at τ*

$\alpha_i, \beta_i, \gamma_i, \delta_i, \varepsilon_i$: *Emission co-efficient of i^{th} thermal unit*

a_i, b_i, c_i, d_i : *Cost co-efficient for i^{th} thermal unit*

e_i, h_i : *Co-efficient of the valve point effect of i^{th} thermal unit*

$C_{(1\text{-}6)j}$: *Hydropower output co-efficient of j^{th} hydro unit*

$P_{ti}^{min}, P_{ti}^{max}$: *Minimum and maximum power limit of i^{th} thermal unit*

$P_{hj}^{min}, P_{hj}^{max}$: *Minimum and maximum power limit of j^{th} hydro unit*

$Q_{hj}^{min}, Q_{hj}^{max}$: *Minimum and maximum discharge limit of j^{th} hydro reservoir*

$V_{hj}^{min}, V_{hj}^{max}$: *Minimum and maximum volume limit of j^{th} hydro reservoir*

$V_{hj}^{min}, V_{hj}^{max}$: *Minimum and maximum volume limit of j^{th} hydro reservoir*

$V_{hj}^{begin}, V_{hj}^{end}$: *Initial and final storage volume of j^{th} hydro reservoir*

1. INTRODUCTION

In the current context, the issue of global warming has emerged as a significant cause for alarm, mainly attributable to the escalating pollution resulting from the extraction of energy from fossil fuels across the world. Moreover, many current energy extraction methods rely heavily on finite fossil fuel supplies. Conversely, renewable resources are associated with certain limitations, such as a relatively low energy density and inherent variability in their availability. Hence, it is imperative to prioritize the scheduling of generation in thermal-renewable energy systems to sustain economic progress while adhering to environmentally conscious practices. The integration of wind energy into the energy industry has become increasingly economically viable, rendering it particularly useful in scheduling.

1.1. Literature Review

The investigation of cost optimization advancement in hydrothermal scheduling has been a subject of study among researchers for a considerable period. Their study proposed a method for ST-HTPS that incorporates an adaptive chaotic differential evolution (DE), genetic algorithm (GA), adaptive chaotic artificial bee colony algorithm, and differential real-coded quantum-inspired evolutionary algorithm [1-4]. A previous study suggested utilizing volatile wind power with superconducting high-temperature superconductors ST-HTPS to meet security constraints. The authors have proposed a classical model for short-term power scheduling of hydro-thermal-wind systems that incorporates uncertainties in wind power and considers economic and environmental restrictions [5-6]. To address the difficulties related to the incorporation of large wind power capacity, researchers have used a bee colony optimization (BCO) technique [7]. The ant lion optimization (ALO) algorithm was proposed to address the challenge of allocating resources for non-conventional forms of generation [8-12]. An empirical method to get the best explanation of hydrothermal-wind scheduling includes the optimization techniques to optimize the generation cost under varying conditions. This algorithm takes into consideration both economic and environmental factors. Scientists have explored many types of empirical algorithm categories to find solutions to problems related to ST-HTWS concerns [13-16]. Some examples of these include the extended NSGA-III [15], particle swarm optimization (PSO) [17], parallel particle swarm optimization (PPSO), gravitational search algorithm (GSA) [18], probability interval optimization (PIO), and several other population-based optimization methods [19-21]. Various empirical algorithms that take their cues from natural occurrences and use random optimization techniques have been developed in recent years. Teaching learning-based optimization (TLBO) is one example of such an algorithm; it has demonstrated encouraging results when used to solve the ST-HTWPS problem [22-23]. Table 1 summarizes several optimization techniques used by different studies in Hydro-Thermal-Wind Scheduling (HTWS).

Table 1 Summarizing various optimization algorithms applied to Hydro-Thermal-Wind Scheduling (HTWS) by different researchers

Optimization Algorithm	Key Features	Reference
Particle Swarm Optimization (MPSO)	Enhanced local search capability; reduced generation cost and emissions	[17], [39], [45], [47], [53]
Improved Cheetah Optimization (ICO)	Addresses renewable uncertainties; integrates wind resources	[55], [56]
Genetic Algorithm (GA)	Reduced generation cost and emissions; high search capability for complex scheduling problems.	[2], [20]
Ant Lion Optimization (ALO)	Effective for large-scale wind-hydro-thermal scheduling problems.	[8], [11], [12]
Artificial Bee Colony (ABC) Algorithm	Cost-effective generation and emissions; high search capability for complex scheduling problems	[3], [7]
Teaching learning-based optimization (TLBO)	Applied to hydro-thermal scheduling with wind energy resources.	[22], [50], [58]
Modified Adaptive Selection Cuckoo Search Algorithm (MASCSA)	Fixed-head short-term model; effective for large-scale systems	[57]
Non-dominated Sorting Gravity Search Algorithm (NSGSA)	Multi-objective optimization handles various constraints effectively	[6], [15], [59]
Hybrid Gravitational Search Algorithm (GSA)	Combines thermal, wind, and hydro frameworks; a hybrid optimization technique	[18], [49], [51]
Chaos-Assisted Sine Cosine Algorithm (CA-SCA)	Incorporates chaos theory; improves local search for global optimal solutions	[60], [61]

The essential purpose of the research was to find ways to cut down on the amount of fuel used by the multi-objective function while still considering a wide variety of complicated constraints. The study results suggest that implementing crisscross optimization (CCO) may significantly decrease fuel expenditures and emissions compared to well-established approaches [24-32]. In addition, improved performance was accomplished by resolving the ST-HTWPS problem, which can be shown in terms of the convergence characteristics and distribution diversity. As a result, it is a strategy that has the potential to be successful in dealing with the problem of ST-HTWPS. A novel approach was introduced to optimize the performance of wind-based hybrid energy systems using a multi-objective stochastic strategy [26]. In addition, the recently introduced opposition-based learning (OBL) approach has been employed to address the load dispatch issue in renewable wind energy systems, increasing convergence speed and performance accuracy in optimization-based scheduling models [27-28]. In this work, [29] described a rapid non-dominated sorting TVAC-PSO to solve multi-objective economic emission dispatch issues. The authors proposed a constraint-handling strategy using the differential evolution algorithm to address the dynamic economic emission dispatch problem [30] and examined the relationship between economic growth and the intensity of carbon dioxide emissions [31].

The author of this essay successfully addressed the issue of short-term hydrothermal scheduling by considering the unpredictable nature of renewable energy sources. Furthermore, the Gram-Charlier formula has been used to ensure the proper distribution of the output random variables [33-40]. The primary purpose of the crow search algorithm (CSA) is to reduce the overall production cost [36]. The primary focus is on the foraging behavior of crows. The CSA method has the benefit of including additional tuning elements with population size and number of repetitions. This aids the algorithm in answering different types of goal functions.

However, decreasing the tuning value will limit the algorithm's maximum capability and hinder performance optimization for a specific objective. The efficacy of the CSA algorithm is assessed by examining several assessment platforms with varying numbers of generating units. The findings were previously evaluated against the ALO [12], MFO [34, 52, 62], Hybrid chemical reaction optimization [63, 64], and DA computations [35, 41]. This study introduces an upgraded version of the Beluga Whale Optimizer (EBWO) [66], Equilibrium Optimizer (EO) [67], Moth-flame Optimizer (MFO) [68], and Chaotic Artificial Ecosystem Optimizer (CAEO) [69] that can handle the economic load dispatch [64] issue in big power systems. It does this by speeding up convergence and improving the quality of the solutions compared to other approaches.

1.2. Research Gap

The research gap is found in the literature review. Although Crisscross Optimization (CCO) seems to have very good results for scheduling problems involving hydro-thermal scheduling coupled with wind energy resources, further research is necessary. Finally, though CCO successfully mitigates hydro-thermal scheduling optimization challenges, its performance in highly dynamic and uncertain environments, and affliction by the impact of lightning-fast weather changes on wind energy, also warrants investigation. Moreover, the applicability of CCO to more complex, real-world energy grids, particularly in large-scale power systems with multiple interdependent renewable sources, has not been fully validated. While most current studies have been based on static or simplistic models, real-time wind energy scheduling, along with rapid fluctuations in water availability across hydro resources and vice versa, necessitates a more adaptive and robust optimization framework. In addition, integrating CCO with advanced methods of forecasting wind [54] and water availability is not been explored extensively for further improving scheduling accuracy. This creates a setting for using CCO-based scheduling methods in a more resilient, responsive, and renewable integrated power system [57].

Even though renewable energy sources are becoming more common in modern power systems, figuring out the best way to schedule multi-source generation, especially when it comes to hydro, thermal, and wind units, remains a difficult and nonlinear problem because renewables are random, there are operational limits, and resources are dependent on each other. When things get this complicated, traditional optimization approaches frequently have trouble with how quickly they converge and how accurate their solutions are. This paper, then, defines the best way to use an integrated hydro-thermal-wind system as a restricted nonlinear optimization problem and suggests a Crisscross Optimization (CCO)-based technique to solve it in the best way possible. The main goal is to keep the system reliable and follow all of its rules while keeping the total generation cost as low as possible.

1.3. Main Contributions

According to the literature review, the main contributions in the proposed work are as follows:

- Enhanced Optimization Efficiency: By showing its ability to efficiently traverse complex, high-dimensional search spaces, CCO has also been able to converge faster and find better solutions to multidimensional hydro-thermal scheduling problems with wind energy integration.
- Improved Cost-Effectiveness: The CCO algorithm provides an optimization of the cost allocation amongst hydro, thermal, and wind resources for still lower operational costs compared to conventional scheduling.
- Greater System Reliability: CCO-based models have improved power supply reliability by incorporating wind energy in the hydro-thermal scheduling process. The algorithm makes sure that no reliance is put on thermal power; rather, it exploits renewable sources of energy.

Moreover, the renewable energy rating matches the overall demand profile and the grid's ability to handle electricity that comes and goes without breaking dependability or stability rules. The grade is also chosen to see how well the CCO algorithm can deal with the unpredictability, fluctuation, and intermittency that come with renewable power. The study makes sure that the CCO algorithm's performance can be fairly and reliably compared by including renewable energy sources with genuine ratings in the optimization problem. This choice helps to fairly evaluate how well CCO works at ensuring cost-effective and dependable dispatch when renewable resources are unreliable and changeable.

The subsequent sections of this work are structured in such a way as to present the mathematical formulation of scheduling that was discussed in Section 2. The Crisscross optimization (CCO) algorithm and its application in the current study are the topics that will be covered in the third section of this paper. The fourth portion of the paper presents an in-depth analysis of the test system and a discussion of how the simulation works and the results. In section 5 of the document, you will find the conclusion to the work.

2. MATHEMATICAL FORMULATION OF ST-HTWPS

The primary objective of this endeavor is to provide a scheduling framework for power generation that integrates hydrothermal, wind, and other forms of renewable energy resources. This framework will include both economic and environmental aspects. The inherent impulsiveness of renewable energy supplies adds another layer of complication to the problem of scheduling generation [42-47].

2.1. Formulation of Multi-objective Function

The amount of electricity a hydroelectric project generates does not affect the facility's price. When planning for hydro-thermal generation, it is essential to factor in the total cost of generation, which considers the cost of coal used in thermal plants and the costs involved with generating electricity from wind sources. In the scenario that has been presented, the primary objective is to achieve the lowest possible value for the objective function, which includes the total cost of generation associated with thermal, wind, and hydropower facilities while simultaneously adhering to all of the system limits that are taken into consideration for scheduling. The following is an illustration of a mathematical formulation that may be applied to explain a regressive multifaceted function:

$$Min...C_T = (F_T, E_T, W_T) \tag{1}$$

$$Min...C_T = \sum_{\tau=1}^{T}\left(\sum_{i=1}^{N_t}(P_{ti,\tau}+E_{i\tau})+\sum_{k=1}^{N_w}(P_{wk,\tau}C_{wk}+OEC_{wk,\tau}+UEC_{wk,\tau})\right) \tag{2}$$

The amount of power that hydroelectric plants can generate can be mathematically described as a function of the head and the reservoir's volume.

$$P_{hj,\tau} = (c_{1j}V_{hj,\tau}^2 + c_{2j}Q_{hj,\tau}^2 + c_{3j}V_{hj,\tau}Q_{hj,\tau} + c_{4j}V_{hj,\tau} + c_{5j}Q_{hj,\tau} + c_{6j}) \tag{3}$$

Where Q_{hj} and V_{hj} represent the water discharge and reservoir storage volume, respectively, of the j^{th} hydro plant during the τ^{th} interval. c_1-c_6 represents the power generation coefficients of the j^{th} hydro plant.

The regressive multifaceted (1) function can be reconstructed as:

$$\text{Minimize } C_T = (F_T + h_i \times E_T + W_T) \tag{4}$$

2.1.1. Economic objective

The fuel cost function in a thermal power plant is represented mathematically as a quadratic function of the actual power production. This representation takes into consideration the impacts of valve points (5). The mathematical elaboration of this idea might be stated as follows:

$$F_T = \sum_{\tau=1}^{T}\left(\sum_{i=1}^{N_t}\left[a_iP_{ti,\tau}^2 + b_iP_{ti,\tau} + c_i + \left|e_i\sin\left(f_i(P_{ti}^{\min} - P_{ti,\tau})\right)\right|\right]\right) \tag{5}$$

2.1.2. Environmental objective

As global air pollution becomes more severe, there is an increased emphasis on protecting the environment and reducing emission pollutants from conventional power units. Burning coal (fossil fuels) is the primary source of pollution emissions in the power system. The combustion of sulfur oxides (SOx) and nitrogen oxides (NOx) may be accurately modeled using a combination of quadratic and exponential functions [49], as seen in Equation (6). The amount of power that can be produced at a coal-fired power station determines the amount of pollution that that facility can release into the atmosphere. The total amount of pollutants released into the environment can be modeled as:

$$E_T = \sum_{\tau=1}^{T}\left(\sum_{i=1}^{N_t}\left[\alpha_i P_{ti.\tau}^2 + \beta_i P_{ti,\tau} + \gamma_i + \varepsilon_i \exp(\delta_i P_{ti,\tau})\right]\right) \text{ lb./hr} \tag{6}$$

2.2. Probability distribution of wind generation

To address the ST-HTWPS issue, our first concern should be devising strategies to manage the inherent unpredictability of wind generation. When attempting to convey the stochastic character of wind speed profiles, the Weibull probability density function (PDF) technique [48] is often used. The PDF of the Weibull distribution may be stated in the following manner:

$$f_v(v) = \left(\frac{s}{c}\right)\times\left(\frac{v}{c}\right)^{(s-1)}.\exp\left(-\left(\frac{v}{c}\right)^{s}\right) \quad (s > 0) \tag{7}$$

Here, C and s are positive values representing the scale-factor and shape-factor, respectively. V represents the present velocity of the wind turbine. The cumulative-density function (CDF) may be derived from the wind speed PDF.

$$F_v(v) = 1 - \exp\left(-\left(\frac{v}{c}\right)^{s}\right) \tag{8}$$

The generation of wind power is dependent on wind velocity, and some researchers employ a linear model to explain the connection between the two variables. This model may be described as follows:

$$w = \begin{cases} 0 & (v < v_{in}, v \geq v_{out}) \\ \dfrac{w_r(v - v_{in})}{(v_r - v_{in})} & (v_{in} < v < v_r) \\ w_r & (v_r \leq v < v_{out}) \end{cases} \tag{9}$$

The v_r, v_{in}, and v_{out} are the rating wind speed, the cut-in wind speed, and the cut-out wind speed. The estimated power of a wind-turbine speed is w_r. $w \in [0, w_r]$ stands for wind power output. According to Equation (10), when the wind speed is positioned between v_{in} and v_r, the P-DF of w may be represented as follows:

$$F_w(w) = \frac{shv_{in}}{w_r c}\left[\left(1 - \frac{hw}{w_T}\right)v_{in}/c\right]^{s-1}.\exp\left\{\left[-\left(1 - \frac{hw}{w_T}\right)v_{in}/c\right]^{s}\right\} \tag{10}$$

where, $h = \left(\frac{v_r}{v_{in}} - 1\right)$.

Eq. (11, 12) is mostly used to represent continuous probability. The expressions for the discrete probability where w = 0 or wr are as follows:

$$P(w=0)=P_r(v<v_{in})+P_r(v>v_{out})=1-\exp\left(-\left(\frac{v_{in}}{c}\right)^s\right)+\exp\left(-\left(\frac{v_{out}}{c}\right)^s\right) \tag{11}$$

$$P(w=w_r)=P_r(v_{in}\le v\le v_{out})=1-\exp\left(-\left(\frac{v_r}{c}\right)^s\right)+\exp\left(-\left(\frac{v_{out}}{c}\right)^s\right) \tag{12}$$

2.3. Generation cost of wind generation

Dissimilarity in wind speed is a highly imperative factor in converting wind energy into usable form. Three distinct aspects go into determining the overall cost of operating and maintaining a wind generator, which is as follows: a) The concept of direct cost refers to the expenses that can be directly ascribed to a particular activity or project. b) Indirect costs cannot be immediately assigned to an activity or project. c) Underestimation cost refers to the potential financial ramifications that may develop due to the expected costs for a project or activity being lower than the actual expenses incurred for that project or activity. d) The term "overestimation cost" refers to the financial ramifications that arise when the expected expenses for a project or activity end up being higher than the actual expenditures that have been incurred [48]. The following is an example of a mathematical equation that may be used to indicate the cost of producing power using a wind generator:

$$W_T=\sum\nolimits_{\tau=1}^{T}\left(\sum\nolimits_{k=1}^{N_w}C_{wk}P_{wk,\tau}+OEC_{wk,\tau}+UEC_{wk,\tau}\right) \tag{13}$$

Extracting useful resources, such as electricity from the wind, is more commonly known as utility extraction. This procedure has a direct cost, a linear function of the power used.

$$C_{wk}(P_{wk,\tau})=\sum_{\tau=1}^{T}\sum_{k=1}^{N_w}d_kP_{wk,\tau} \tag{14}$$

The primary determinant of wind power prediction accuracy is the degree of uncertainty associated with the availability of wind energy. The penalty cost-function for overestimating the kth wind power may be expressed as follows.

$$\begin{gathered}OEC_{wk,\tau}=c_{o,k}.w_{k,\tau}\left[1-\exp\left(-\left(\frac{v_{in,k}}{c_k}\right)^{s_k}\right)+\exp\left(-\left(\frac{v_{out,k}}{c_k}\right)^{s_k}\right)\right]+\left(\frac{w_{r,k}v_{in,k}}{v_{r,k}-v_{in,k}}\right)\\ \left[\exp\left(-\left(\frac{v_{in,k}}{c_k}\right)^{s_k}\right)-\exp\left(-\left(\frac{v_1}{c_k}\right)^{s_k}\right)\right]+\left(\frac{w_{r,k}c_k}{v_{r,k}-v_{in,k}}\right)\\ \left\{\Gamma\left[1+\frac{1}{k_k}\left(\frac{v_1}{c_k}\right)^{s_k}\right]-\Gamma\left[1+\frac{1}{k_k}\left(\frac{v_{in,k}}{c_k}\right)^{s_k}\right]\right\}\end{gathered} \tag{15}$$

The penalty cost-function associated with the underestimation of the kth wind power may be expressed in the following manner.

$$UEC_{wk,\tau} = c_{u,k}.(w_{r,\tau} - w_{k,\tau})\left[1-\exp\left(-\left(\frac{v_{r,k}}{c_k}\right)^{s_k}\right)+\exp\left(-\left(\frac{v_{out,k}}{c_k}\right)^{s_k}\right)\right]+$$
$$\left(\frac{w_{r,k}v_{in,k}}{v_{r,k}-v_{in,k}}+w_{k,\tau}\right)\left[\exp\left(-\left(\frac{v_{r,k}}{c_k}\right)^{s_k}\right)-\exp\left(-\left(\frac{v_1}{c_k}\right)^{s_k}\right)\right]+ \tag{16}$$
$$\left(\frac{w_{r,k}c_k}{v_{r,k}-v_{in,k}}\right)\left\{\Gamma\left[1+\frac{1}{s_k}\left(\frac{v_1}{c_w}\right)^{s_k}\right]-\Gamma\left[1+\frac{1}{s_k}\left(\frac{v_{in,k}}{c_k}\right)^{s_k}\right]\right\}$$

The variables $OEC_{wk,\tau}$, and $UEC_{wk,\tau}$ represent the expenses associated with overestimation and underestimation, respectively. The cost coefficients are represented by the variables $C_{o,k}$, and $C_{u,k.}$ The wind generator's rated speed, cut-in, and cut-out wind speeds are denoted as $v_{r,k}$, $v_{in,k}$, and $v_{out,k}$, respectively. The rated wind output power is denoted as $w_{r,k}$. The notation represents the power generated by the wind at the τ^{th} time interval.

2.4. Non-linear Constraints

The operational limits of the generator are the primary component of the restrictions that are related to ST-HTWPS. Additional limitations encompass the capacity of the storage reservoir and restrictions on discharge levels, another important constraint. The hydrological equilibrium within the reservoir is shown in the following manner.

$$V_{hj,\tau} = V_{hj,\tau-1} + I_{hj,\tau} - Q_{hj,\tau} - S_{hj,\tau} + \sum\nolimits_{m}^{R_{uj}} Q_{hm(\tau-t_{mj})} + S_{hm(\tau-t_{mj})} \tag{17}$$

The initial reservoir-storage volume is, and the final reservoir-storage volume is.

$$V_{hj,0} = V_{hj,begin} \tag{18}$$

$$V_{hj,\mathrm{T}} = V_{hj,\mathrm{end}} \tag{19}$$

The maximum allowable generation for thermal power units is given as

$$P_{ti}^{\min} \le P_{ti} \le P_{ti}^{\max} \qquad (i{=}1,2,3....N_t) \tag{20}$$

The maximum allowable hydropower is given as

$$P_{hj}^{\min} \le P_{hj} \le P_{hj}^{\max} \qquad (j{=}1,2,3....N_j) \tag{21}$$

The maximum allowable generation of wind power units is given as

$$0 \le P_{wk} \le P_{wk}^{rated} \qquad (k=1,2,.....N_w) \tag{22}$$

The maximum allowable storage volume for the reservoir is listed below.

$$V_{hj,\tau}^{\min} \le V_{hj,\tau} \le V_{hj,\tau}^{\max} \tag{23}$$

The maximum amount of water that can be released from the reservoir is listed below.

$$Q_{hj,\tau}^{\min} \le Q_{hj,\tau} \le Q_{hj,\tau}^{\max} \tag{24}$$

The power balancing constraint for the power system can be written as:

$$\sum_{i=1}^{N_t} P_{ti,\tau} + \sum_{j=1}^{N_h} P_{hj,\tau} + \sum_{k=1}^{N_w} P_{wk,\tau} = P_{D,\tau} + P_{L,\tau} \tag{25}$$

3. CRISSCROSS OPTIMIZATION

The crisscross optimization (CCO) technique, which is detailed in reference [38], is a population-based heuristic approach that has shown excellent efficiency in solving non-convex optimization problems with a high number of dimensions. Employing two interdependent crossover operators is one of the distinguishing characteristics of CCO. This is because horizontal crossover and vertical crossover work in tandem. The horizontal crossover method is a method that is used to find a novel solution by investigating a subset of the population, precisely half of the population, which is separated into different hyper-cubes. The method's name comes from the fact that it crosses over from one subset of the population to another. As one approaches closer to the cores of these hyper-cubes, the possibility of discovering a new answer becomes progressively less likely. The probability is highest near the edges of the hypercube. It is common knowledge that employing a cross-border strategy is an efficient way to reduce the impact of blind spots and enhance one's ability to conduct global searches. Vertical arithmetic crossover, on the other hand, is utilized by the vertical crossover technique to deliver unique solutions. The difference between vertical crossover and horizontal crossover may be seen very clearly. This distinctive characteristic is crucial in preserving population variety and enabling the departure from regional minimums in fixed dimensions. The employment of both crossover operators, which generate offspring solutions according to the parent solutions, ultimately leads to the generation of a moderation solution during each iteration of the process. By the concept of "survival of the fittest," moderation solutions are utilized to modify the pre-existing dominant solutions within parent populations. This stage is essential for ensuring the presence of solutions that have enhanced fitness values and is, therefore, very important.

The choice of Crisscross Optimization (CCO) as the best dispatch approach for integrated hydro-thermal-wind scheduling is based on its unique ability to solve difficult, nonlinear, and very limited optimization issues that are frequent in multi-source power systems. CCO uses both horizontal and vertical crossover algorithms, which lets it do a strong global search while keeping the solution space diverse. This two-dimensional search method helps CCO avoid converging too soon and makes it better at finding numerous optimum areas at the same time. CCO is different from classic algorithms like GA, PSO, or DE since it keeps a good balance between exploration and exploitation. This makes it perfect for dynamic and unpredictable situations like wind-integrated systems.

CCO is also computationally efficient since it needs fewer control parameters and converges faster, which is important for scheduling in real time or close to real time. It can handle both discrete and continuous variables, which makes it perfect for mixed-integer hydro-thermal scheduling issues. Because of these benefits, CCO is a strong and new way to find cost-effective, dependable, and environmentally friendly dispatch solutions in modern power systems.

Thus, employing a CCO technique makes it easier for individuals to rapidly converge on their personal best fitness values, as shown in Figure 1. The flowchart of the implemented CCO algorithm is depicted in Fig. 2. The stages involved in the development of CCO are as follows.

Step 1: Initialize
To enhance the efficiency of a problem-solving process, a Computational Search Optimization (CCO) algorithm first generates a population.

$$P = \{P^m\} \; m = 1, 2, ...M \text{ , where } P^m = (P_1^m, P_1^m, ...P_D^m) \quad (26)$$

P can be generated by

$$P_i^m = P_i^{\min} + \mu_i (P_i^{\max} - P_j^{\min}) \; i=1,\, 2 \ldots D;\; m=1,\, 2 \ldots M \quad (27)$$

Step 2: The second step entails carrying out a horizontal crossover plan with an organization that is in direct competition with you. In the case that we have been presented with, the individuals that are contained within the set *P* are split up into pairs without any repetition, namely *M/2* pairings, to make the process of horizontal crossover more manageable. To carry out the horizontal crossover procedure at the dth dimension, The process of moderation helps to select the most appropriate response.

$$\begin{aligned} &\left\{ MH^i(d) = r_1 P^i(d) + (1 - r_1).P^j(d) + C_1.\left(P^i(d) - P^j(d)\right) \right. \\ &\left\{ MH^j(d) = r_2 P^j(d) + (1 - r_2).P^i(d) + C_2.\left(P^j(d) - P^i(d)\right) \right. \end{aligned} \quad (28)$$

As a result, the CCO algorithm keeps a population in *X* that is made up of individuals' best replies.

Step 3: Carry out the crossing by making use of the alternative operator.
Random pairing of the dimensions that make up set *P* ensures that no two dimensions will ever appear together in the same pair. Let us take into consideration a situation in which the dimensions d_1 and d_2 that are paired together are employed in the process of accomplishing vertical crossing. The solution for moderation is constructed based on

$$MV^m(d_1) = r.P^m(d_1) + \; (1 - r).P^m(d_2);\; m \in N(1, M),\; d_1,\; d_2 \in N(1, D) \quad (29)$$

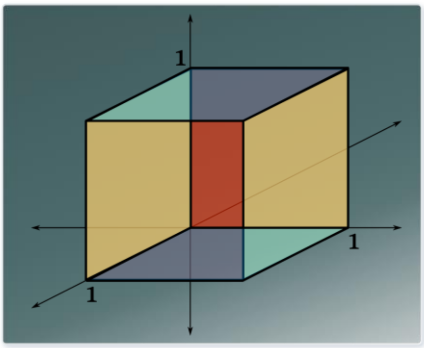


Fig. 1 Diagrammatic representation of the crisscross optimization (CCO) algorithm

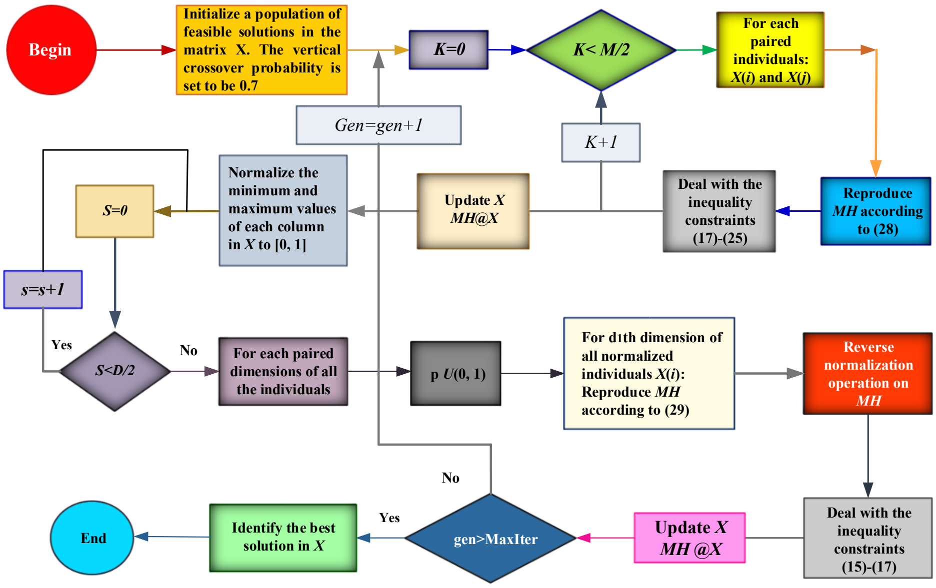


Fig. 2 Flow chart of the crisscross optimization (CCO) for power scheduling

The use of moderation tactics employing vertical crossover faces opposition from comparable parental strategies that are the product of horizontal crossover. Those persons with better overall fitness values have a greater chance of being passed down to the next generation.

Step 4: The procedure ends when the total number of iterations has reached a number that is more than the one that was determined in advance. Alternately, the procedure that was explained in step 2 is carried out once more in order to kick off yet another cycle.

4. SIMULATION AND TEXT RESULTS

A standard illustration investigation system is considered to address the issue of short-term hydrothermal power scheduling (ST-HTPS) systems with many objectives related to economic and emission dispatch. The algorithm in question has been subjected to testing utilizing two case studies. The first case study investigates incorporating four hydroelectric facilities and three thermal plants to address the economic emission issue in hydrothermal scheduling. The second structure contains four hydroelectric facilities, three thermal units, and two wind power plants. It aims to address the economic-emission dilemma by optimizing the ST-HTWPS. The case studies are categorized into three cases:

- Test method-01 focuses on minimizing costs.
- Test method 02 focuses on reducing emissions.
- Test method-03 focuses on concurrently reducing both costs and emissions.

At first, wind energy needs to be taken into account. Subsequently, wind energy will evaluate the effectiveness of the proposed CCO in a renewable setting. Every case study consists of a population of 50 individuals and undergoes 100 iterations. The computational approach is implemented on a MATLAB system, using a 4.0 GHz Core i3 CPU and 8GB of RAM. The program is run 100 times independently using 50 different beginning trial solutions. Only a few basic, intricate limitations have been quantified for ST-HTPS and ST-HTWPS system challenges.

Only a few ST-HTPS systems and ST-HTWPS system situations have been successfully resolved by using a cutting-edge meta-heuristics technique. Currently, RER, such as hydro and thermal power plants, play a vigorous role in meeting the electricity mandate. Updates are provided on an ongoing schedule throughout the scheduling stage, which will continue for twenty-four hours. Two investigations were replicated to evaluate the effectiveness of the proposed method. One of the case studies did not include wind or RER, while the other included wind and RER.

4.1. Case Investigation 01 (CI-01)

The test system CI-01 includes three conventional thermal units and four hydropower units without considering any renewable energy resources (RER), as seen in Figure 3. The factors about generation, reservoir inflows, reservoir capacity limitations, maximum/minimum limits, and cost coefficients for thermal units are obtained from [3]. Transmission losses are not considered in this testing system, even though the thermal cost characteristic shows non-linear behavior owing to the valve-point loading feature. This case study is divided into three separate incidents.

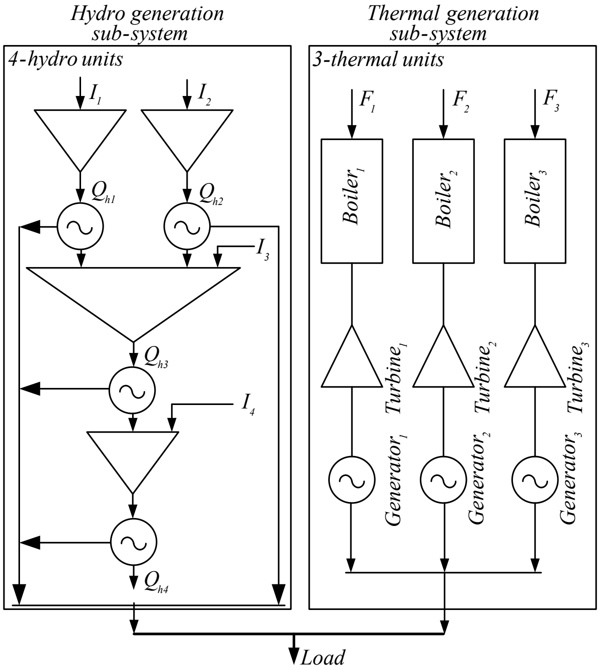


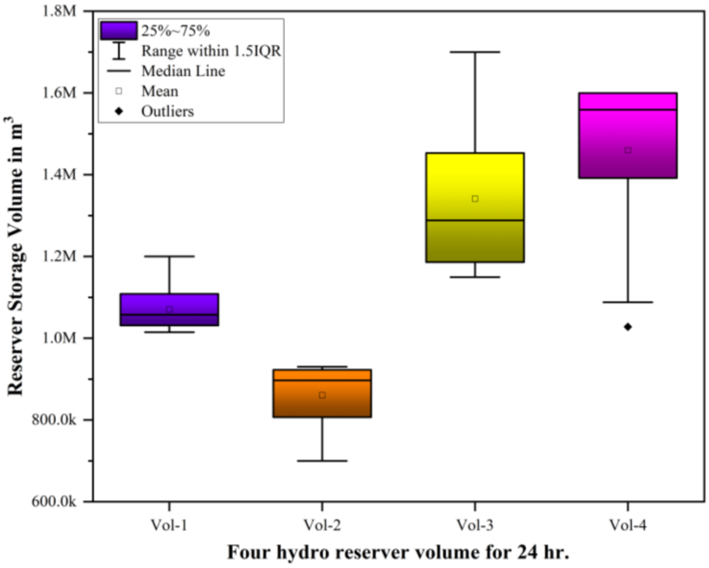
Fig. 3 Diagrammatic representation of the hydro-thermal testing system CI-01

4.1.1. Test Method I (fuel-cost minimization)

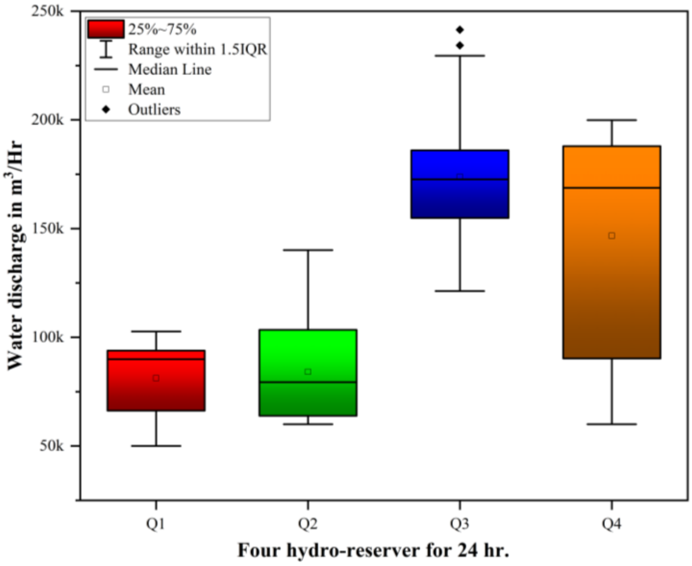
With a single objective, the CCO method determines the optimal allocation for the ST-HTPS optimization problem. Table 2 displays the outcomes of the effort to reduce generating expenses, namely the ideal generation timetable for the conventional power plant and the hydropower output achieved using CCO. The statistical information and calculation period of the suggested CCO findings for cost reduction, excluding renewable energy, are compared with other available approaches and shown in Table 3. However, it is comprehensible that the CCO algorithm perfectly converges to the optimal result. Fig. 4 (a) and (b) display the optimal hourly water storage capacity and volume required for the hydro reservoir in this particular case. The outcomes derived by the anticipated algorithm have been contrasted with the reported discoveries using other approaches. Considering the achievable outcome, it can be inferred that CCO is more appropriate for attaining an affordable minimum cost and requires less time than other existing methods.

Table 2 Presents the most efficient levels of thermal power production and hydropower production for minimizing costs without considering using the CCO method to use renewable wind energy

Time in Hr.	Hy1 (MW)	Hy2 (MW)	Hy3 (MW)	Hy4 (MW)	Th1(MW)	Th1(MW)	Th1(MW)
1	82.34996	51.62096	21.71404	129.1189	104.3904	131.2409	229.5648
2	70.9624	51.17042	10.28265	125.7369	175	206.9534	139.8942
3	71.95079	52.81381	13.9876	121.6183	175	124.9725	139.657
4	67.21491	58.47275	19.72644	115.8148	32.99822	124.9725	230.8004
5	65.73583	55.08114	29.30316	132.0747	33.11741	124.9725	229.7153
6	61.23068	57.91508	37.14257	147.0691	57.04139	209.6156	229.9856
7	87.79727	63.1818	39.49368	230.2641	175	124.9848	229.2784
8	85.79307	68.35469	38.58265	260.0959	27.01957	210.318	319.8361
9	85.91687	67.58953	37.08858	277.8742	175	126.1144	320.4164
10	84.18538	58.53919	36.32249	286.1361	175	209.9249	229.8919
11	86.96655	68.58016	37.20514	281.2498	102.1319	293.7177	230.1487
12	83.40514	58.15905	35.75671	280.7408	175	288.1214	228.8169
13	81.46426	72.5412	35.25713	285.6706	107.1775	208.4463	319.443
14	86.90983	76.67428	34.29559	288.088	103.4314	210.3182	230.2827
15	84.40494	67.17055	34.64887	287.7098	101.4741	293.5584	141.0334
16	85.89357	85.19179	40.17236	294.6071	24.27035	209.9249	319.9399
17	86.26866	81.80878	44.67332	301.7656	175	130.7233	229.7603
18	84.29073	77.71197	46.43186	295.827	174.8902	210.3304	230.5178
19	83.68343	78.90653	51.24953	302.2907	23.64089	210.704	319.5249
20	80.51589	75.61435	51.6293	298.3168	103.3708	211.5057	229.0472
21	56.05703	67.65449	55.81235	290.5454	175	124.9725	139.9583
22	59.84314	70.71232	57.94359	292.4803	21.73874	124.9725	232.3094
23	54.7231	78.7645	58.82192	286.0587	104.8025	124.9725	141.8568
24	57.0482	52.76623	58.73778	263.3245	102.7213	124.9725	140.4295



(a)



(b)

Fig. 4 Display of the (a) hourly water storage volume and (b) water discharge to minimize costs without using wind energy, using the CCO method

Table 3 Presents a comparison between the results obtained using CCO and other strategies used for minimizing costs, excluding the consideration of renewable wind energy

Technique & Ref. No.	Min.-Cost ($)	Max.-Cost ($)	Aver.-Cost ($)	Computational Time (Sec.)
CCO (Proposed)	41371.69	41946.56	41978.61	36
MFO [62]	41 526.5172	41 587.0654	41 554.83	32
DGSA [49]	41751.15	41989.02	41821.49	NA
GSA [49]	42032.05	42561.33	42292.12	NA
QTLBO [63]	42 187.49	42 202.75	42193.46	NA
TLBO [50]	42385.88	42441.36	42407.23	NA
PSO [53]	44 740	NA	NA	NA

4.1.2. Test Method II (Emission minimization)

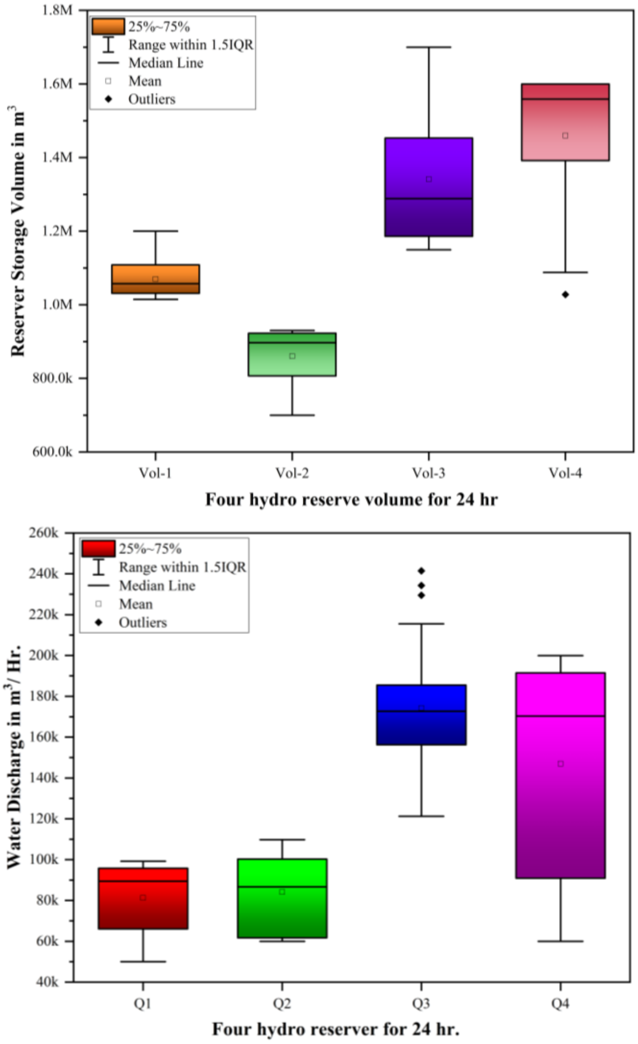
This instance addresses the issue of reducing emissions in a hydro-thermal scheduling dilemma. Table 4 presents data on thermal power production and hydropower generation from four hydropower facilities during 24 hours and the overall emissions. Table 5 displays the minimum, maximum, and mean costs, and it also includes a comparison of the acquired result with alternative approaches. It is widely acknowledged that the projected CCO methodology is the most effective method for producing minimal emissions. The modeling results indicate that the CCO achieves a minimal emission of 15734.33lb/day. Fig. 5(a) and (b) display the most favorable outcome of reservoir water discharge and water storage volumes hourly to minimize emissions, respectively.

Table 4 Presents the ideal thermal power production and hydropower generation for minimizing emissions, without taking into account the use of renewable wind energy, using the CCO method

Time in Hr.	Hy1 (MW)	Hy2 (MW)	Hy3 (MW)	Hy4 (MW)	Th1 (MW)	Th1 (MW)	Th1 (MW)
1	78.87328	50.164	21.71404	129.0269	168.9897	180.1799	121.0522
2	73.35526	51.296	10.28265	125.7437	174.9936	202.5578	141.771
3	73.07815	52.934	13.68387	121.6253	155.7855	169.6382	113.255
4	69.36228	54.5	19.4749	115.8221	146.1229	147.6699	97.04794
5	63.1538	55.504	29.13267	132.0812	145.5344	148.2544	96.33955
6	61.89578	55.994	37.10496	147.0748	175	190.2568	132.6737
7	84.53714	58.30791	39.0819	231.6519	175	213.7578	147.6633
8	86.09648	62.07581	38.1848	258.8731	175	229.4978	160.272
9	86.22017	70.53495	36.22514	277.8694	175	256.3263	187.824
10	85.22001	72.94326	35.08504	285.7396	175	245.0882	180.9239
11	87.39169	74.87321	35.45502	281.0596	175	253.8372	192.3832
12	86.9426	79.0939	34.09318	280.8159	175	280.22	213.8344
13	86.67401	76.14701	36.34646	285.5845	175	255.2437	195.0043
14	86.64343	71.35457	34.53627	288.1877	175	219.9445	154.3335
15	85.1528	66.54898	37.23805	287.8094	175	209.9249	148.3259
16	85.47116	72.23995	42.66399	292.4633	175	227.3267	164.8349
17	84.70514	73.43224	46.86387	292.2227	175	220.0647	157.7114
18	84.27968	78.87701	48.61953	300.8899	175	251.8293	180.5046
19	81.96494	76.51016	50.29585	301.8065	175	226.5294	157.8932
20	81.95271	73.39096	51.96423	301.1372	175	216.3576	150.1973
21	54.60137	68.52931	56.1088	292.2992	160.0964	163.355	115.0099
22	54.30295	69.64238	58.17977	290.0736	146.8056	144.6988	96.29692
23	54.70582	69.77855	58.9341	289.3679	139.2172	144.1013	93.89514
24	55.11188	67.43993	58.57885	282.4274	130.0656	124.9725	81.40393

Table 5 Comparing the outcomes of CCO with other established methods for reducing emissions, excluding the use of renewable wind energy

Technique & Ref. No.	Min.-Emission (lb)	Max.-Emission (lb)	Aver. -Emission (lb)	Computational Time (Sec.)
CCO (Proposed)	15734.33	15799.23	15775.49	23
MFO [62]	15 849.42	15 897.08	15 870.44	21
PSO [53]	16 928.00	NA	NA	NA
IGA [64]	17 659.00	NA	NA	NA
DE [65]	18 257.00	NA	NA	NA



(a)

(b)

Fig. 5 Display the (a) water discharge and (b) hourly water storage capacity to minimize emissions without relying on wind energy using the Crisscross Optimization (CCO) method

4.1.3. Test Method III (simultaneously fuel cost-emission minimization)

In this scenario, the feasibility of the proposed approach for a complex system is assessed by considering multi-objective cost-emission minimization. Table 6 presents thermal power production and hydropower generation data for 24 hours. Table 6 displays the total cost of generation, pollutant emissions, and a comparison of the performance of the suggested approach, CCO, and other heuristic algorithms, along with statistical research. The use of CCO in this situation aims to simultaneously decrease fuel expenses and emissions. For this lesson, the CCO algorithm produced a cost of 42233.72$/day and emissions of 15922.24lb//day. Upon comparison, it is evident that the numerical solution obtained by CCO is superior in addressing the fuel cost and emission reduction challenge. Fig. 6 (a) and (b) display the most favorable outcome of hourly reservoir storage volume and water discharge amounts to minimize combined cost emission (CCE), respectively. The comparative findings acquired via the implementation of advanced CCO in hydro-thermal scheduling, when compared to the results obtained using other approaches, demonstrate the higher performance of the CCO approach in terms of fitness value. Table 7 shows the comparison between the obtained outcomes with other strategies.

Table 6 The objective is to achieve the most efficient thermal power and hydropower production while minimizing costs and emissions. This analysis does not consider the use of renewable wind energy and is based on the use of CCO

Time in Hr.	Hy1 (MW)	Hy2 (MW)	Hy3 (MW)	Hy4 (MW)	Th1 (MW)	Th1 (MW)	Th1 (MW)
1	78.8732	50.164	21.7140	129.026	175	155.597	139.624
2	71.0102	51.296	10.2826	125.743	175	207.840	138.826
3	71.4465	52.934	13.6838	121.625	175	124.972	140.337
4	67.3937	54.5	19.3111	115.822	128.312	124.972	139.688
5	65.9139	55.504	28.8618	132.081	123.031	124.972	139.635
6	60.7082	55.994	36.7290	147.074	175	185.062	139.431
7	86.6082	67.7982	38.8506	231.651	175	209.924	140.166
8	86.2119	65.6319	37.8818	258.873	175	246.448	139.952
9	86.4171	67.7649	36.0828	277.869	175	217.058	229.803
10	84.7070	61.8039	35.6012	285.739	175	209.924	227.223
11	87.2710	71.9957	36.2792	281.059	175	218.392	230.002
12	85.0919	65.4952	34.7489	280.815	175	280.22	228.628
13	86.9419	74.1406	34.4737	285.396	175	224.842	229.204
14	90.7615	83.3652	35.9729	288.882	175	215.150	140.867
15	84.0541	76.2732	35.7138	287.739	175	209.924	141.294
16	78.6286	63.9248	41.2808	292.391	175	210.448	198.325
17	87.2363	79.5754	47.4212	295.596	175	210.866	154.303
18	84.5292	76.1644	48.3946	296.577	175	210.029	229.305
19	84.3935	74.8203	49.7491	303.545	175	211.245	171.246
20	83.8326	77.4574	54.4389	300.800	175	211.505	146.964
21	54.6505	67.5485	56.4514	291.488	175	124.972	139.888
22	54.3427	69.7298	58.4348	289.213	123.918	124.972	139.388
23	55.4218	74.7276	59.3612	288.506	107.358	124.972	139.651
24	57.5934	64.1448	55.9512	261.269	102.721	124.972	133.347

Table 7 Comparing the outcomes of CCO with other established methods for reducing fuel cost along with emissions, excluding the use of renewable wind energy

Technique & Ref. No.	Cost ($)	Emission (lb)	Computational Time (Sec.)
CCO (Proposed)	42233.72	15922.24	36
MFO [62]	42957.30	16319.85	34
PSO [53]	43280.00	17899.00	NA
IGA[64]	43507.00	18183.00	NA
DE [65]	51449.00	18257.00	NA

4.2. Case Investigation 02 (CI-02)

The present investigation integrates two wind farms with four hydro and three thermal facilities to provide uninterrupted 24-hour electricity generation. The input information for the hydropower and thermal power plants is the same as that utilized in a previous test system. Case investigation 02 is divided into three separate cases, as seen in Fig. 8.

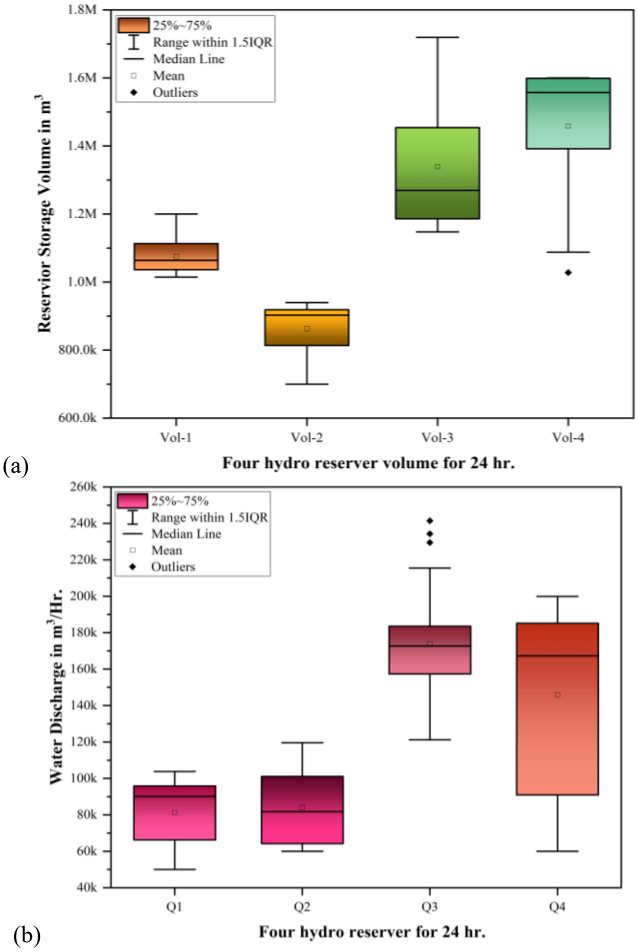


Fig. 6 Display of the (a) water discharge and (b) hourly water storage volume to minimize costs and emissions, excluding wind energy, using CCO

The cost of wind power production is compared to the cost of conventional power generation to establish the most economically efficient solution for the short-term hydro-thermal-wind power scheduling (ST-HTWPS) system problem using the CCO technique. In this case, the constraints associated with generation are also measured.

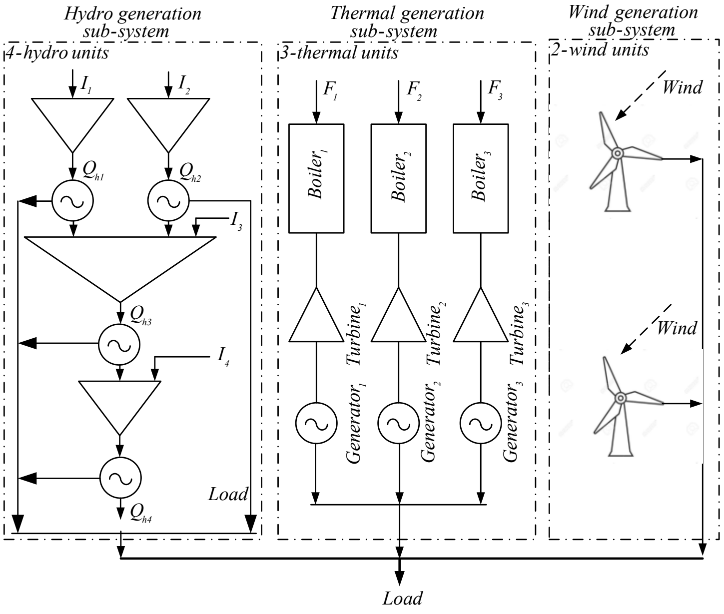


Fig. 7 A diagrammatic representation of the hydro-thermal-wind testing system CI-02

4.2.1. Test Method I (fuel cost minimization)

The technology has gotten more intricate in integrating the two wind plants. Table 8 displays the most favorable result of CCO, including thermal power production, hydroelectricity production, and two instances of wind energy production during 24 hours. Constraints related to generation are also taken into account in this scenario. The CCO technique has been used to reduce the production cost of the ST-HTWS issue in this research. The cost of generating wind power has been compared against the cost of generating thermal electricity to determine the most cost-effective solution for the ST-HTWS issue using the CCO approach. The fuel cost per day is 36,698.51 dollars after including sustainable wind energy. Two wind farms are implemented to reduce generating costs, resulting in a decrease from $41,371.69 per day to $36,698.51 per day. The optimal amount of hourly hydro reservoir storage volume, water discharge, and cost of generating without and with wind power necessary to reduce expenses when using renewable energy via CCO, respectively, are shown in Fig. 8(a), 8(b), and 8(c).

4.2.2. Test Method II (emission minimization)

In this scenario of minimizing emissions for a single target, Table 9 displays the best thermal power production, hydropower generation, wind power generation from two wind parks, total emissions, and computing time. The emission minimization issue yielded an emission value of 7523.51 lb/day. The introduction of a renewable wind park has resulted in a reduction in emissions from 15734.33lb/day to 7523.51 lb/day. The appropriate amount of hourly hydro reservoir storage capacity, water discharge, and Comparison of the emissions of producing without wind power and with wind power, necessary to reduce emissions while utilizing renewable energy via the use of CCO, respectively, Fig. 9 (a), (b), and (c).

Table 8 Minimizing costs by considering sustainable sources of energy, utilizing CCO to achieve the most efficient thermal power production and hydropower generation

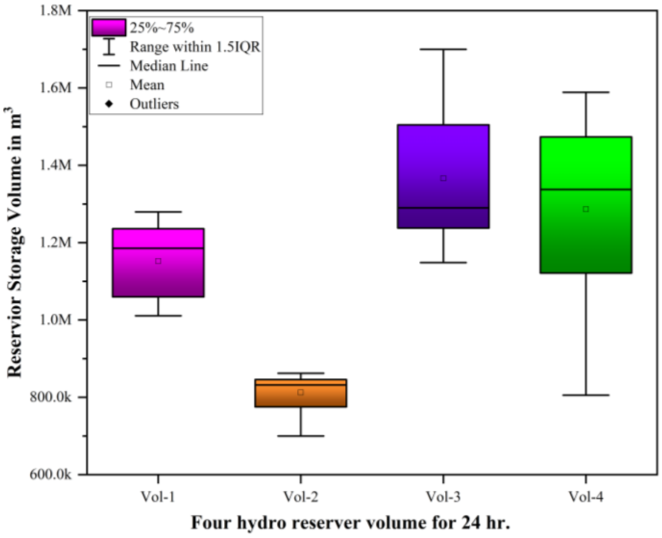
Time in Hr.	Hy1 (MW)	Hy2 (MW)	Hy3 (MW)	Hy4 (MW)	Th1 (MW)	Th2 (MW)	Th3 (MW)	Wind (MW)	Wind (MW)
1	68.23104	62.34391	0	204.1296	103.0865	128.1996	51.71791	85.79294	46.49856
2	54.39438	54.20014	47.129	145.2817	98.72844	42.24949	228.9479	77.60342	31.46555
3	87.92805	59.18572	13.74829	143.1487	101.469	123.5045	58.19579	63.47785	49.34216
4	54.67036	59.43523	20.07592	182.9842	21.7847	124.3117	51.76608	81.32062	53.65122
5	64.33563	62.54392	15.3165	216.7433	23.69196	123.9242	50.18993	55.80375	57.45073
6	95.56229	53.6379	41.89075	142.156	97.94814	203.5361	53.3146	75.3889	36.56528
7	69.76729	55.89449	12.67233	133.5461	100.0292	212.1856	228.9866	88.21601	48.70237
8	64.065	59.70791	47.60813	243.8188	102.2694	48.41055	319.1312	73.98812	51.00101
9	84.93205	72.23897	46.96064	208.5733	101.7381	125.3388	326.5706	78.19169	45.45585
10	63.81429	71.83588	48.24117	225.2803	104.9828	209.3749	231.6657	84.8357	39.9692
11	63.62341	71.43757	39.11371	248.1565	106.6513	207.3219	228.4033	79.35661	55.93573
12	85.7322	61.87032	0	273.2108	102.813	124.9014	412.79	69.7123	18.96989
13	79.68963	67.62984	3.595648	214.1325	101.9094	205.1761	309.1214	88.27308	40.47237
14	99.61933	68.4253	47.34515	182.3541	99.86839	124.4908	321.9465	41.71591	44.23457
15	68.41951	57.87026	47.2887	274.3525	102.6287	126.0594	229.5729	65.89373	37.9144
16	101.9683	77.91309	51.51937	271.3694	20.24162	210.127	226.7933	85.97291	14.095
17	69.8205	74.34571	50.53525	182.8383	104.9847	125.9732	320.2835	71.0032	50.21554
18	68.51215	66.73316	40.34393	280.8712	24.87304	296.6179	233.5362	80.23199	28.28054
19	58.04335	59.90756	54.63872	249.7896	101.3402	130.2584	316.708	74.79899	24.51517
20	84.81127	58.25321	55.56613	275.4606	21.71315	125.0294	316.91	67.55746	44.69876
21	68.98439	60.97019	41.82101	251.9223	107.6216	208.0338	52.28718	78.53748	39.82195
22	99.38626	49.74386	57.33057	282.9644	20.35326	128.122	137.5414	40.16902	44.38919
23	88.42073	73.1809	55.64921	238.3938	21.15011	125.9365	139.727	69.83921	37.70267
24	99.03009	79.16993	58.40116	275.279	20.52057	209.9957	50.61244	1.768879	5.222166

4.2.3. Test Method III (simultaneously fuel cost-emission minimization)

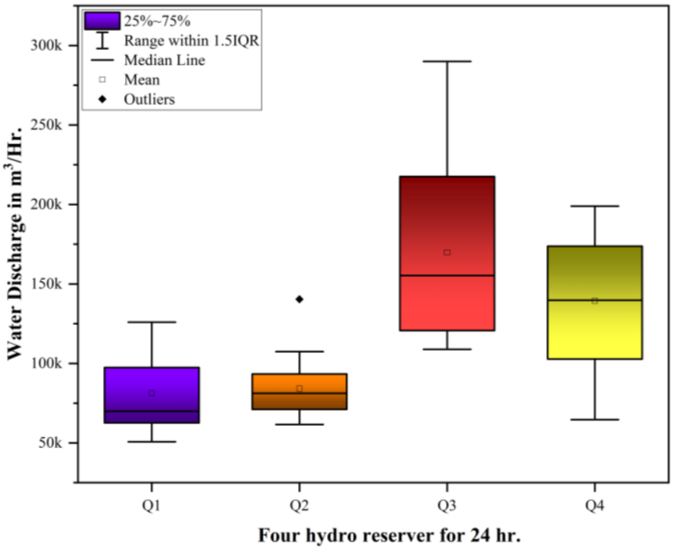
A hydro-thermal system is subjected to an experiment that explicitly targets wind energy to enhance the cost-effectiveness of production and minimize emissions. The study determines the optimal values for economic performance and pollutant emissions by considering thermal power generation, hydropower generation, and wind production from 02 wind parks. The cost and emission resulting from the CCO algorithm for this lesson are 36,389.25 $/day and 9,436.29 pounds per day, respectively, and the results are presented in Table 10. Figures 10 (a), (b), and (c) illustrate the optimal storage capacity, water discharge, and a comparative analysis of the costs and emissions associated with hydroelectric generation both with and without wind power, utilizing CCO on an hourly basis. The advantage of CCO is evident as it not only outperforms other approaches but also demonstrates the highest likelihood of providing a better solution. Fig. 11 displays the convergence characteristics of several algorithms, such as CCO, MFO, traditional PSO, and GA, about the total fuel cost of case investigation-02.

Table 9 Using sustainable wind power using CCO to maximize thermal power production, and hydroelectric generation to minimize emissions

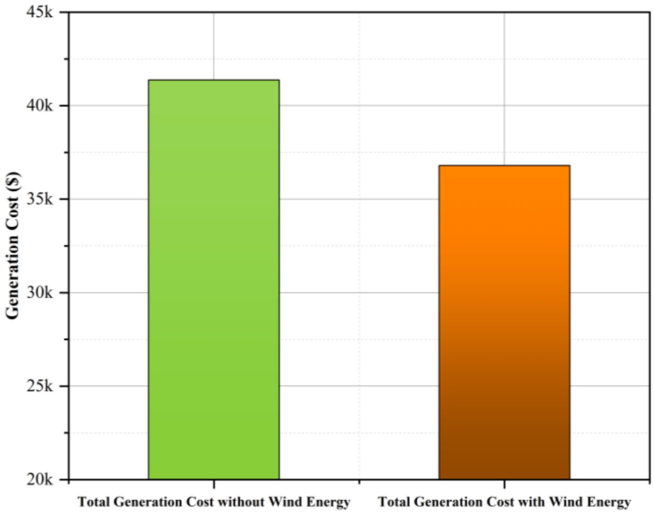
Time (Hr.)	Hy1 (MW)	Hy2 (MW)	Hy3 (MW)	Hy4 (MW)	Th1 (MW)	Th2 (MW)	Th3 (MW)	Wind (MW)	Wind (MW)
1	75.39496	52.88065	45.66188	131.9891	111.4903	121.1451	65.00599	89.54004	56.89198
2	77.04883	51.69261	42.54009	133.5077	126.8138	119.6619	82.21709	89.03796	57.48012
3	60.71715	53.60738	27.10024	124.1605	122.1386	97.36992	71.40527	89.07327	54.42765
4	58.42392	54.61237	33.98216	122.9965	103.5391	79.08661	55.8926	86.71419	54.75253
5	62.52747	56.4381	26.9883	130.286	108.056	71.96016	70.28943	87.49572	55.95884
6	69.83083	56.13634	49.76662	147.8062	124.6684	119.3	93.88517	89.27455	49.33186
7	87.4691	69.24262	25.02598	162.517	162.1847	172.6871	129.3198	89.89012	51.66367
8	88.30119	59.45911	19.11318	273.0836	152.6201	145.2905	123.7236	89.22691	59.1817
9	80.41932	64.02155	48.25578	202.0907	158.4464	167.7131	224.4275	88.45241	56.17325
10	94.49908	69.19991	36.18133	282.7335	165.8513	176.8705	148.9654	89.67371	52.2067
11	84.7244	73.39848	32.31843	268.2429	168.3839	194.5487	130.3814	88.44947	59.5523
12	85.63268	76.02932	47.62899	287.057	145.3751	167.5888	196.2311	88.70096	55.75603
13	86.65185	75.57371	49.01018	278.7418	159.4365	170.5004	141.5338	89.11456	59.43719
14	85.77098	75.25064	36.18133	292.8345	152.3505	140.4802	98.14338	89.38271	59.60574
15	78.26127	68.95598	27.72763	295.1743	143.7796	155.3238	91.11824	89.70257	59.95663
16	86.84995	78.04301	19.11318	286.0802	160.8835	165.8276	135.2643	89.3944	57.65707
17	86.61084	71.79016	48.8594	286.2898	149.5176	157.29	104.7365	88.8699	56.03567
18	86.69031	79.23211	49.72707	287.8209	169.3341	165.8069	135.312	89.04787	57.02886
19	85.25303	76.61337	53.71111	295.0136	144.0439	161.1534	112.7581	86.68383	54.76961
20	69.32807	73.36118	55.34942	300.6679	141.0053	144.774	116.015	89.50146	59.99766
21	64.91076	60.38749	56.63485	294.8878	118.8278	103.8436	65.13814	87.96321	57.40622
22	68.42799	49.67967	50.31076	282.6576	109.5326	94.25565	70.00989	89.35652	45.76931
23	61.04988	58.72951	59.31696	274.6163	91.92485	101.5344	59.70285	89.51227	53.61292
24	59.62238	63.49379	53.56546	277.5293	73.98308	80.93718	59.85418	88.62176	42.39292



(a)

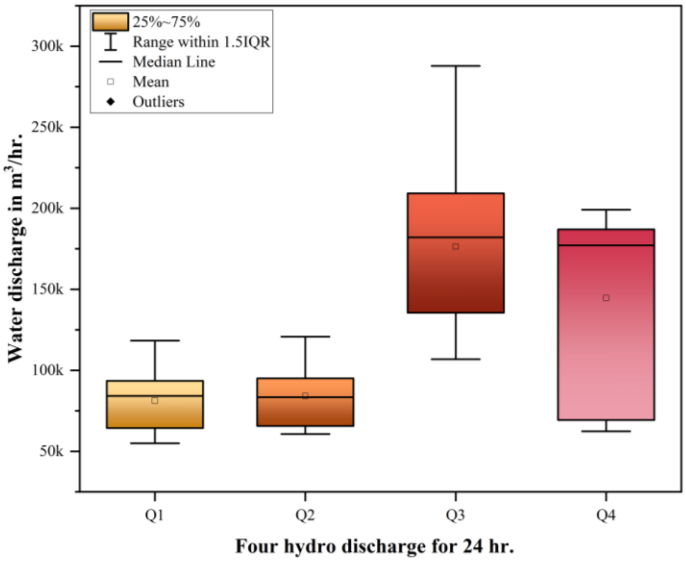


(b)

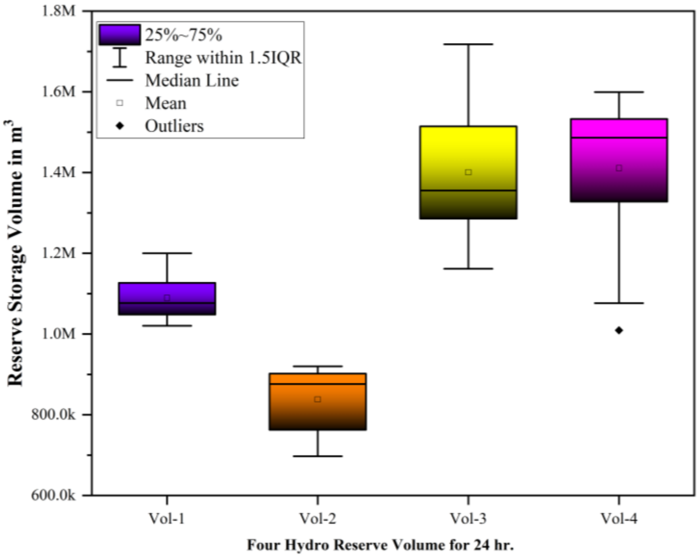


(c)

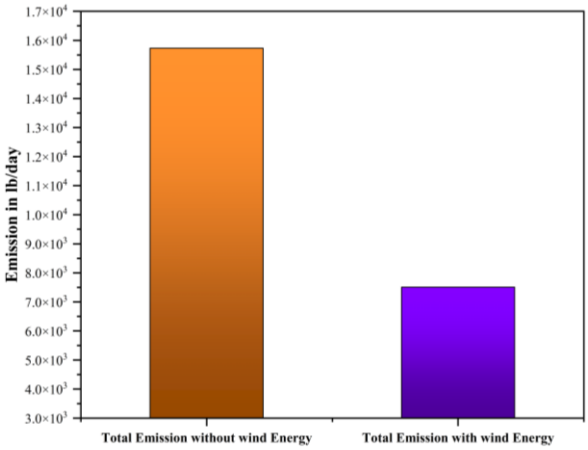
Fig. 8 Optimizing (a) water discharge and (b) hourly water storage capacity to minimize costs while using wind energy via the use of CCO, (c) Comparison of the cost of generating without wind power and with wind power using CCO


25%~75%
Range within 1.5IQR
Median Line
Mean
Outliers
300k
250k
200k
150k
100k
50k
Water discharge in m³/hr.
Q1
Q2
Q3
Q4
Four hydro discharge for 24 hr.

(a)


1.8M
1.6M
1.4M
1.2M
1.0M
800.0k
600.0k
25%~75%
Range within 1.5IQR
Median Line
Mean
Outliers
Reserve Storage Volume in m³
Vol-1
Vol-2
Vol-3
Vol-4
Four Hydro Reserve Volume for 24 hr.

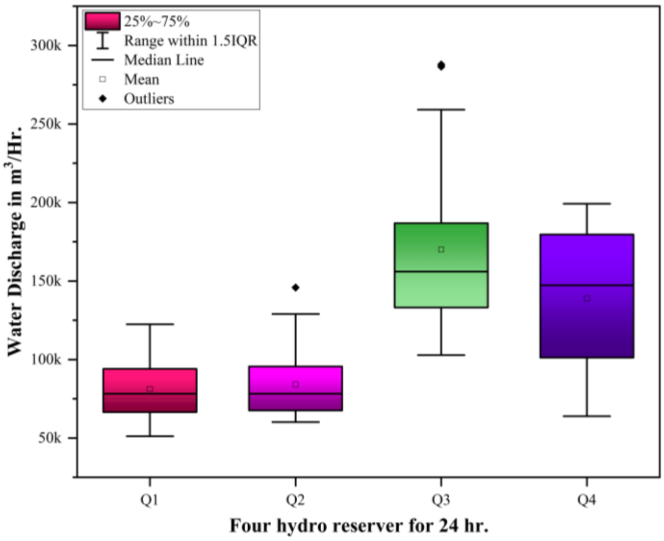
(b)



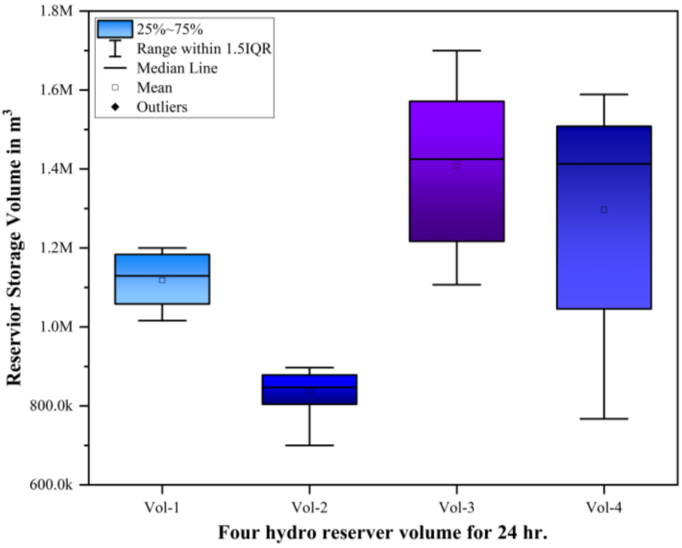
(c)

Fig. 9 Optimizing (a) water discharge and (b) hourly water storage volume to minimize emissions with the use of wind energy and the use of CCO, (c) Comparison of the emissions of generating without wind power and with wind power using CCO

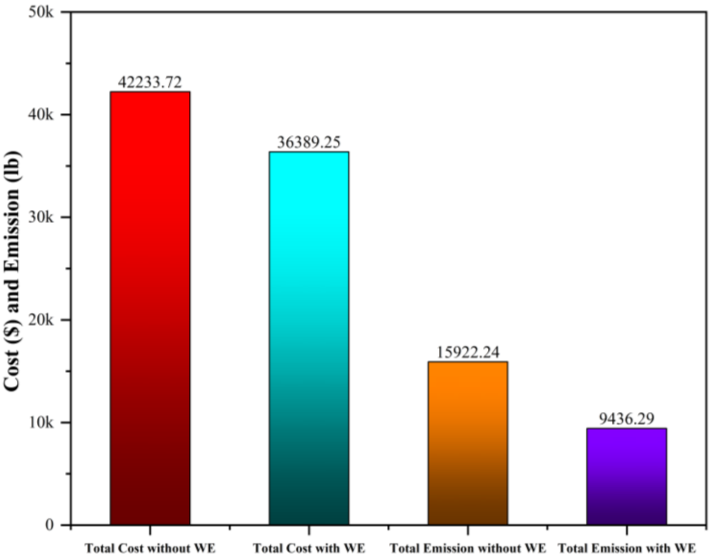
The suggested Crisscross Optimization (CCO)-based dispatch technique might be improved for future research by adding more renewable sources, including solar photovoltaics and biofuels, to make it more sustainable. Adding uncertainties using stochastic or resilient optimization frameworks will make the model even more useful when wind and load demands change in the real world. You may also look at combining the dynamics of charging electric vehicles (EVs) with demand-side management tactics to show how smart grids are changing. Also, using the CCO algorithm in real-time energy management systems or hardware-in-the-loop simulations would provide us more information about how it works in the actual world and how well it works.



(a)



(b)



(c)

Fig. 10 Optimizing (a) water discharge and (b) hourly water storage volume to minimize cost and emissions with the use of wind energy and the use of CCO, (c) Comparison of the cost and emissions of generating without wind power and with wind power using CCO

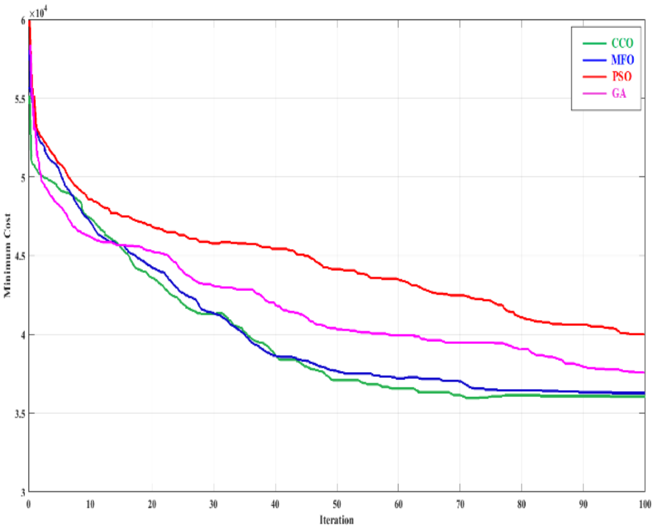


Fig. 11 Cost of test system fuel, convergence of CCO, MFO, PSO, and GA algorithms

Table 10 Maximizing cost-emission reduction by using renewable wind energy via CCO to optimize thermal power production and hydropower generation

Time in hr.	Hy1 (MW)	Hy2 (MW)	Hy3 (MW)	Hy4 (MW)	Th1 (MW)	Th2 (MW)	Th3 (MW)	Wind (MW)	Wind (MW)
1	62.9479	51.5116	57.9512	171.928	103.217	40.9853	138.510	87.6273	35.3203
2	71.3790	51.2641	33.3096	212.247	105.640	42.3669	136.569	68.0549	59.1679
3	68.3026	60.2224	38.6922	186.070	106.434	41.4839	61.7021	88.7284	48.3627
4	68.2911	65.2915	49.6575	123.418	104.556	46.9465	57.2230	88.6253	45.9899
5	70.5634	67.8239	43.9500	100.670	120.258	121.669	50.5774	88.4124	50.0246
6	92.3948	72.8699	39.3633	189.444	102.383	128.789	67.0338	88.9296	58.1541
7	59.1842	55.8229	39.3633	147.785	162.455	206.947	174.568	88.8482	54.3877
8	78.2655	53.7974	45.9759	147.129	173.826	125.210	247.968	89.1537	48.6711
9	93.8400	53.1355	44.0573	236.909	171.890	206.323	179.817	89.4828	58.6013
10	67.4585	54.5879	43.9500	164.77	170.484	209.715	229.344	88.4043	51.2843
11	97.0011	76.8480	45.2944	286.276	104.445	208.455	138.134	87.7092	55.8346
12	59.9033	63.7116	39.3633	261.414	164.072	208.349	209.953	87.5651	55.6675
13	77.3947	68.6174	48.4663	253.908	172.578	135.500	216.582	87.5192	49.4321
14	90.1716	64.7897	44.057	220.464	112.820	209.793	140.199	89.5191	58.1842
15	87.3950	75.6613	51.1745	284.856	101.610	129.415	140.351	83.3308	56.2045
16	90.6642	59.8826	50.2195	257.206	106.719	211.832	137.270	88.608	57.5967
17	86.2627	65.7796	54.4133	291.170	104.511	210.622	135.352	87.0993	14.7878
18	69.4250	85.1076	53.5570	241.394	166.695	211.172	150.115	87.4615	55.0702
19	85.0426	73.7729	55.5769	284.540	111.925	204.038	112.002	86.0883	57.0130
20	77.6312	65.0152	53.0736	286.302	164.063	124.745	136.756	83.8387	58.5732
21	55.9878	66.6099	49.7797	251.090	101.717	123.944	135.57	71.8285	53.4716
22	67.8621	59.1569	55.6102	274.685	102.772	124.003	51.7784	78.5602	45.5709
23	84.8829	72.6984	58.6730	207.792	99.6234	130.906	55.4749	88.7484	51.1999
24	88.9454	80.2636	58.8243	283.955	103.331	128.562	52.3178	3.08535	0.71456

5. CONCLUSION

Most nations have a limited fossil fuel energy resource that will soon run out. Power architecture professionals are working to switch to renewable energy sources to address this issue. The environmental requirements make hybrid power systems useful for study, as they utilize clean energy and contribute to a greener environment. This work optimizes a hybrid power structure multi-objective problem using the CCO method. The computational findings indicate that the intended CCO method is suitable for further study. CCO yields the best result and exceeds other algorithms in solution quality, robustness, and processing economy. This method speeds up convergence and makes solutions more accurate while keeping a balance between exploration and exploitation. The suggested model takes into account real-time operational restrictions, such as water balance equations, ramp rate limits, and wind uncertainty, to make sure that scheduling is realistic and efficient. As far as we know, this is the first time that CCO has been used for multi-source energy coordination. It has been shown to work better than other state-of-the-art algorithms in terms of lowering costs and making the system more reliable. Due to its success in optimizing wind-based power systems, the suggested method is recommended for hybrid power systems that use renewable sources, including fuel cells, e-vehicle charging, biomass, and more. The results of the simulation show that the proposed CCO modelling is a better choice than older heuristic methods when it comes to money (36389.25 $/day) and lower emissions (9436.29 lb/day). CCO Pareto optimal solutions are of better quality and distributed. CCOs' mean CPU time to develop 30 scheduling schemes is also lower than existing optimization approaches, indicating their efficiency and real-time computing capabilities. This research work provides an innovative and efficient solution to the complex short-term hydro-thermal-wind power scheduling problem.

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