Chaos-infused wind power integration in the grey wolf optimal paradigm for combine thermal-wind power plant systems

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This research presents a novel methodology for tackling the combined thermal-wind economic load dispatch (ELD) issue in contemporary power system. The proposed approach involves hybridizing active-set algorithm (ASA), interior point algorithm (IPA) and sequential quadratic programming (SQP) into grey wolf optimization (GWO) algorithm, while effectively incorporating the intricacies associated with renewable energy sources (RES). A more accurate model is made possible by hybridization for complex systems with memory and hereditary characteristics. The GWO is used as a tool for global search while ASA, IPA and SQP methods are used for rapid local optimization mechanism. The performance evaluation of the design heuristics is carried out on 37 thermal and 3 wind power generating units and outcomes endorse the effectiveness of the proposed scheme over state-of-the-art counterparts. The worthy performance is further validated on statistical assessments in case of thermal-wind integrated ELD problem in terms of measure of central tendency and variation on cost and complexity indices.

KEYWORDS

grey wolf optimization, interior point algorithm, active set algorithm, sequential quadratic programming, economic load dispatch problem, stochastic wind

1 Introduction

There has been observed a drastic increasing demand of electrical energy due to recent developments in domestic, commercial and industrial infrastructures over the past few decades. In this regard, public utility electric supply companies are forced to operate power grid nearly at full load capacities. Under such heavily stressed conditions there will be substantial generational, operational and maintenance costs. Furthermore, there will be an increased power losses, stability and power breakdown matters. In today's modern power system optimal ELD has been given considerable importance owing to the increased electrical energy generation cost and depletion of fossil fuels used in thermal power generating units. The basic aim of ELD

problem is to optimally allocate the active power generation output from thermal power generating units while taking care of the operational constraints associated with power system. By reducing the generation cost and increasing system's reliability through optimal active power allocation, the overall energy capabilities of electrical energy generation increase. The research community has greater interest to approach the conventional ELD problem realistically due to numerous practical scenarios associated with power system. The input-output fuel cost generation curve is basically non-differentiable, non-convex and non-linear owing to the multilevel steam generating valves associated with modern steam operated thermal power generating units commonly known as VPLE. The systematic opening of these steam valves generates ripples in fuel-cost characteristics curve and can be modelled by imposing absolute sine term in main quadratic function of ELD problem (Kaboli and Alqallaf, 2019). There has been observed a greater emission of toxic gases such as carbon-mono-oxide (CO), Sulphur oxide (SO) and nitrogen oxide (NO_x) as a result of electrical power generation from fossil fuels operated thermal power generating units. Due to these hazardous environmental concerns, mathematical formulations have been developed to reduce generation cost and emission levels of above-mentioned toxic gases simultaneously (Yu et al., 2018). The addition of alternate energy resources such as wind and solar energies have rectified the concerns of higher generation cost and emission levels of toxic gases to a greater extent. The integration of renewable energy resources into thermal power plants has led to modifications of conventional quadratic fuel cost characteristic equation by adding Beta and Weibull distribution functions that addresses the stochastically varying behavior of solar and wind power availability respectively (Jiang et al., 2015a; Jadoun et al., 2018). There are some physical limitations associated with some of the generating unit shaft's bearings due to amplified vibrations occurring in some regions of shaft's rotational axis. These prohibited operating zones (POZs) are encountered by introducing disjoint sub regions in input-output fuel cost characteristics function making it non-convex and non-linear optimization problem (Jeddi and Vahidinasab, 2014). The physical phenomenon associated with dynamic ELD problem is encountered by using ramp rate handling strategy during different hours of the day by including upper and lower ramp limits for thermal power generating units (Sattar et al., 2020). Conventional based numerical techniques are not able to solve constrained optimization problems owing to the stiff situations introduced as a result of considering practical constraints in conventional ELD problem. These techniques are unable to produce global optimum outcomes and are often trapped in local optimum regions. In this regard various nature inspired global optimum techniques have been developed over the years to address global optimum stagnation. Particle swarm optimization (PSO) is metaheuristic nature inspired global technique adopted to find optimal results of ELD integrated with stochastic wind (SW) forming hybrid energy generating units (Eberhart and Kennedy, 1995; Jeyakumar et al., 2006; Jiang et al., 2015b; Pandit et al., 2015). Genetic algorithm (GA) is exploited to deal with ELD integrated with physical constraints

where numerical techniques failed to give global optimum outcomes (Chopra and Kaur, 2012). More stable and précised results were recorded using hybrid genetic algorithm (HGA) by appropriate scheduling of active power generation outputs (Balamurugan et al., 2014). Combined economic emission multi-objective load dispatch problem is implemented using differential evolution (DE) based strategy (Balamurugan et al., 2014). IEEE 03, 06 and 13 thermal generating based ELD problem is implemented using Improved tabu search algorithm (ITSA) in (Senthil and Manikandan, 2010). Evolutionary programming (EP) strategy has been found an effective mechanism to counter non-linear and stiff scenarios of ELD problems in (Sinha et al., 2003). Six units-based hybrid energy generating units are exploited using modified version of ant colony optimization (ACO) in (Gopalakrishnan and Krishnan, 2013). Recently developed hybrid imperialistic competitive sequential quadratic programming (HIC-SQP) has been applied to optimize the stochastic behavior in terms of direct cost, overestimated cost and underestimated cost of wind power availability integrated with thermal power generating units in order to reduce generation cost as well as emission of toxic gases simultaneously (Morshed and Asgharpour, 2014). Additionally, recently developed meta-heuristics-based searching algorithms have been applied in power and energy sectors reported in (Abbassi et al., 2019; El-Fergany et al., 2019; Mohseni et al., 2019; Zhang et al., 2020a; Fathy, 2020; Yang et al., 2020).

Development of biological inspired meta heuristic strategy of GWO developed by Mirjalili (Mirjalili et al., 2014; Faris et al., 2018) is fascinating methodology to be applied to stiff scenarios of practical ELD problem. Numerous preponderant problems of optimization are addressed using GWO (Alzubi et al., 2019; Salgotra et al., 2019; Zhang et al., 2020b) that includes feature selection (Chantar et al., 2020), vehicular adhoc networks (Fahad et al., 2018), power system stabilizer design (Shakarami and Davoudkhani, 2016), hydro-power prediction (Dehghani et al., 2019) and energy management (Jiang, 2021; Yang et al., 2022).

In proposed research, the global optimum capabilities through biological inspired meta-heuristics paradigm of GWO algorithm integrated with SQP, ASA and IPA are effectively applied on hybrid energy generating units of thermal and wind power. According to recent survey, the metaheuristic strategy of GWO has not been applied so far on SW problems of ELD. The salient features of proposed research can be categorized as.

- To optimally allocate the active power generation output from thermal generating units and wind power units to reduce the overall fuel generation cost and wind power generation cost.
- Comparative studies of GWO heuristics hybridized with SQP, ASA and IPA outcomes with up-to-date solvers for validating and verifying the strength of proposed hybridized schemes.

The paper is laid out as follows.

The paper is organized with mathematical formulation for ELD problem with VPLE and integrated SW in Section 2 followed by methodologies of GWO algorithm and applications for ELD and SW in Sections 3, 4 respectively.

2 System model formulation

This study involves system model of 40 thermal power generating units containing VPLE and 37 thermal power generating units with an integration of renewable energy in the form of 3 wind power producing plants.

2.1 Quadratic fuel cost function

The main objective/fitness function reflecting input output characteristics between active power generation in MW and fuel generation cost in \$/hr. Can be modelled using quadratic fuel cost function as expressed in Eq. 1 (Kaboli and Alqallaf, 2019).

$$C_1 = \sum_{m=1}^{tg} \left(A_m + B_m P_m + C_m P_m^2 \right). \tag{1}$$

C_1 is total fuel cost generation in \$/hr. whereas tg is total number of thermal power generating units. Generation coefficients reflecting the social, economic and other related terms are being shown by coefficients "A", "B" and "C" for mth thermal power generating unit in quadratic fuel cost formulation.

2.2 Quadratic fuel cost function including VPLE

For flexible power generation operation, each thermal unit is equipped with a series of steam operated valves that allows controlled injection of steam on turbines as per load demand (Kaboli and Alqallaf, 2019). This physical phenomenon can bemodelled with an introduction of absolute and sine terms in quadratic fuel cost function making it non smooth function due to ripples involved with VPLE as shown in Eq. 2.

$$C_2 = \sum_{m=1}^{tg} \left(A_m + B_m P_m + C_m P_m^2 + abs\left(E_m . \sin\left(F_m \left(P_{m,\min} - P_m \right) \right) \right) \right). \tag{2}$$

Where E_m and F_m are generation coefficients involved with VPLE.

2.3 Wind power generation availability cost function

The significant advantage of integrating SW power in thermal power generating units is reflected by economic and environmentally friendly electrical power generation. In power generation system comprising of both thermal and wind power generating units, there have been developed various models for characterizing the scheduling of real power generation and operational generation cost. Due to inherent random speed of wind power, power generation operator is uncertain regarding its availability. He may overestimate wind power availability where actual power is less than that of power predicted and extra power is purchased to fulfill the load requirements. Sometimes

due to underestimation of wind power availability some extra power is available and compensation is provided to wind power supplier's cost for not utilizing the complete wind power available. Total generation cost of wind power can be modelled as shown in Eq. 3 (Morshed and Asgharpour, 2014).

$$C_3 = \sum_{n=1}^{wg} \left[\left(C_{W.P(DIR,n)} \right) + \left(C_{W.P(OE,n)} \right) + \left(C_{W.P(UE,n)} \right) \right] \tag{3}$$

C_3 is total wind power generation cost and wg is total number of wind power generation units. $C_{W. P (DIR, n)}$, $C_{W. P (OE, n)}$ and $C_{W. P (UE, n)}$ are terms associated with direct cost, over-estimated cost and under-estimated cost associated with wind power generating units. Output wind power generation is directly proportional to $C_{W. P (DIR, n)}$ and can be expressed mathematically for nth wind power generation unit as expressed in Eq. 4.

$$C_{W.P(DIR,n)} = \sum_{n=1}^{wg} \left(q_n {}^* W.P_n \right) \tag{4}$$

In Eq. 4 q_n is coefficient expressing direct electrical energy cost from nth wind power generating unit in \$/MWh whereas W. Pn is real electrical output power in MW from nth wind power generating unit. $C_{W. P (OE, n)}$ is unbalanced over-estimated cost as a result of overestimation of wind power availability, so some extra real power in MW is purchased due to electrical power shortage from wind power generating units and can be expressed mathematically as shown in Eq. 5.

$$C_{W.P(OE,n)} = \sum_{n=1}^{wg} \left(C_{rw,n} {}^* X \left(V_{oe,n} \right) \right). \tag{5}$$

$C_{rw, n}$ is cost coefficient for overestimation in \$/MWh for nth wind power generating unit whereas X ($V_{OE, n}$) is expected value of wind power overestimation for nth wind power generating unit and can be expressed mathematically in Eq. 6.

$$\begin{aligned} X(V_{OE,n}) = W.P_n & \left[1 - \exp\left(-\frac{V_{IN,n}^{K_n}}{C_n^{K_n}} \right) + \exp\left(-\frac{V_{OUT,n}^{K_n}}{C_n^{K_n}} \right) \right] \\ & + \left(\frac{W.P_{r,n} {}^* V_{IN,n}}{V_{r,n} - V_{IN,n}} + W.P_n \right) . \left[\exp\left(-\frac{V_{IN,n}^{K_n}}{C_n^{K_n}} \right) - \exp\left(-\frac{V_{1,n}^{K_n}}{c_n^{k_m}} \right) \right] \\ & + \left(\frac{W.P_{r,n} {}^* C_n}{V_{r,n} - V_{IN,n}} \right) \left\{ \Gamma\left[1 + \frac{1}{K_n}, \left(\frac{V_{1,n}}{c_n} \right)^{K_n} \right] - \Gamma\left[1 + \frac{1}{K_n}, \left(\frac{V_{IN,n}}{C_n} \right)^{K_n} \right] \right\}. \end{aligned} \tag{6}$$

V_{IN}, V_{OUT} and V_r are cut-in, cut-out and rated speed of wind in meters per second whereas $V_1 = V_{IN} + (V_r - V_{IN})$ *W. P_1/W. P_r being intermediary parameter. C_n and K_n are coefficients of Weibull distribution reflecting scale and shape factor for nth wind power generating unit. W. P_n and W. P_r are generated and rated electrical power in MW for nth wind power generating unit. Moreover, the incomplete gamma function having two parameters and can be mathematically expressed in Eq. 7 as follow (Liu and Xu, 2010a).

$$\Gamma(p,c) = 1/\Gamma(c) {}^* \int_0^P t^{c-1} e^{-t} dt. \tag{7}$$

While a standard gamma function involves a single parameter expressed as shown in Eq. 8.

$$\Gamma(p) = \int_0^p t^{p-1}e^{-p}dt. \tag{8}$$

$C_{W. \ P \ (UE, \ n)}$ is the penalty cost imposed as a result of underestimating the availability of wind power where the actual active power available out of wind power generating units is more than that of predicted active power. Compensation in this regard is provided to wind power supplier's cost as expressed in Eq. 9.

$$C_{W.P(UE,n)} = \sum_{n=1}^{wg}\left(C_{ew,n} * Y(V_{UE,n})\right). \tag{9}$$

$C_{ew,n}$ is cost coefficient for underestimation in \$/MWh for nth wind power generating unit, $Y(V_{UE,n})$ is expected value of wind power underestimation for nth wind power generating unit and can be expressed in Eq. 10.

$$
\begin{aligned}
Y(V_{UE,n}) = {}& (W.P_{r,n} - W.P_n)\left[\exp\left(-\frac{V_{r,n}^{K_n}}{C_n^{K_n}}\right) - \exp\left(-\frac{V_{OUT,n}^{K_n}}{C_n^{K_n}}\right)\right] \\
& + \left(\frac{W.P_{1,n} * V_{IN,n}}{V_{r,n} - V_{IN,n}} + W.P_n\right) \cdot \left[\exp\left(-\frac{V_{r,n}^{K_n}}{C_n^{K_n}}\right) - \exp\left(-\frac{V_{1,n}^{K_n}}{c_n^{kn}}\right)\right] \\
& + \left(\frac{W.P_{r,n} * C_n}{V_{r,n} - V_{IN,n}}\right)\left\{\Gamma\left[1 + \frac{1}{K_n}, \left(\frac{V_{1,n}}{c_n}\right)^{K_n}\right] - \Gamma\left[1 + \frac{1}{K_n}, \left(\frac{V_{r,n}}{C_n}\right)^{K_n}\right]\right\}.
\end{aligned} \tag{10}
$$

2.4 Overall objective function

The overall objective function can be modelled by combining quadratic fuel cost function involving V.P.L.E (C_2) and wind power generation availability cost function (C_3) as total generation cost (TGC) in \$/hr as shown in Eqs 11, 12.

$$TGC = C_2 + C_3. \tag{11}$$

$$
TGC = \sum_{m=1}^{tg}\left[\begin{array}{c} A_m + B_m P_m + C_m P_m^2 + \\ abs\left(E_m\sin\left(F_m\left(P_{m,\min} - P_m\right)\right)\right) \end{array}\right] \\
+ \sum_{n=1}^{wg}\left[\begin{array}{c} (q_n * W.P_n) + (C_{rw,n} * X(V_{oe,n}) + \\ (C_{ew,n} * Y(V_{UE,n}) \end{array}\right] \tag{12}
$$

2.5 Operational constraints

2.5.1 Load demand constraint

The most important constraint to be handled properly while optimizing total generation cost is that the total active power generation output from different thermal and wind power generating units should be equal to total load demand as expressed in Eq. 13.

$$\sum_{m=1}^{tg}(P_m) + \sum_{n=1}^{wg}(W.P_n) = P_{demand}. \tag{13}$$

2.5.2 Active power generation's constraint

Active power generation output from each thermal and wind power generating unit should be less than or equal to its maximum generation limit and should be greater than or equal to its minimum generation limit such that.

$$P_{m,\min} \le P_m \le P_{m,\max}. \tag{14}$$

$$0 \le W.P_n \le W.P_{r,n}. \tag{15}$$

In Eq. 14 "$P_{m, \ min}$" and "$P_{m, \ max}$" are active power generation limits for mth thermal power generating unit while "W. $P_{r, \ n}$" is rated active power generation for nth wind power unit in Eq. 15.

3 Design methodology

Global search-based technique dependent on GWO algorithm hybrid with local search-based techniques of SQP, ASA and IPA adopted for rapid local convergence is applied to solve constrained optimization problem of power generating system. For evaluating the efficiency and performance of designed hybridized scheme two case studies consisting 40 thermal generating units and 3 wind power generating units are considered. Figure 1 shows proposed work methodology.

3.1 Grey wolf optimization (GWO)

GWO algorithm is newly developed population based meta heuristic algorithm proposed by Mirjalili (Mirjalili et al., 2014). GWO algorithm gets its inspiration from social hierarchy of grey wolves (Canes lupus) which belongs to Canidae family. They usually are known as apex predators meaning they are among top of ranking in food chain. Usually, they live in a pack consisting 5–12 members on an average. It has been observed that grey wolves usually adopt very strict socially dominating hierarchy. The leaders in a pack are alphas. They are responsible for making decisions regarding sleeping, time to wake, and hunting, etc. Decisions made by alphas are strictly implemented throughout the pack. However, some democratic system is also implemented regarding some issues in which alpha follows the decisions of other wolves in a pack. All other wolves acknowledge the dominancy of alphas in a pack by holding their tails down. Alpha wolves in a pack may not be considered as a strongest wolf in a pack but the best one in managing the daily basis affairs of the pack. Alphas are responsible for maintaining strength and discipline in a pack.

The subordinate wolves in a pack are betas. They are second in line after alphas, playing role of advisors to alphas and help alphas in decision making. Betas may be either male or female and are responsible for implementing decisions made by alphas to other wolves in downstream and gives regular feedback regarding decision's implementation to alphas. Betas are considered as fittest candidates to replace alphas in case if
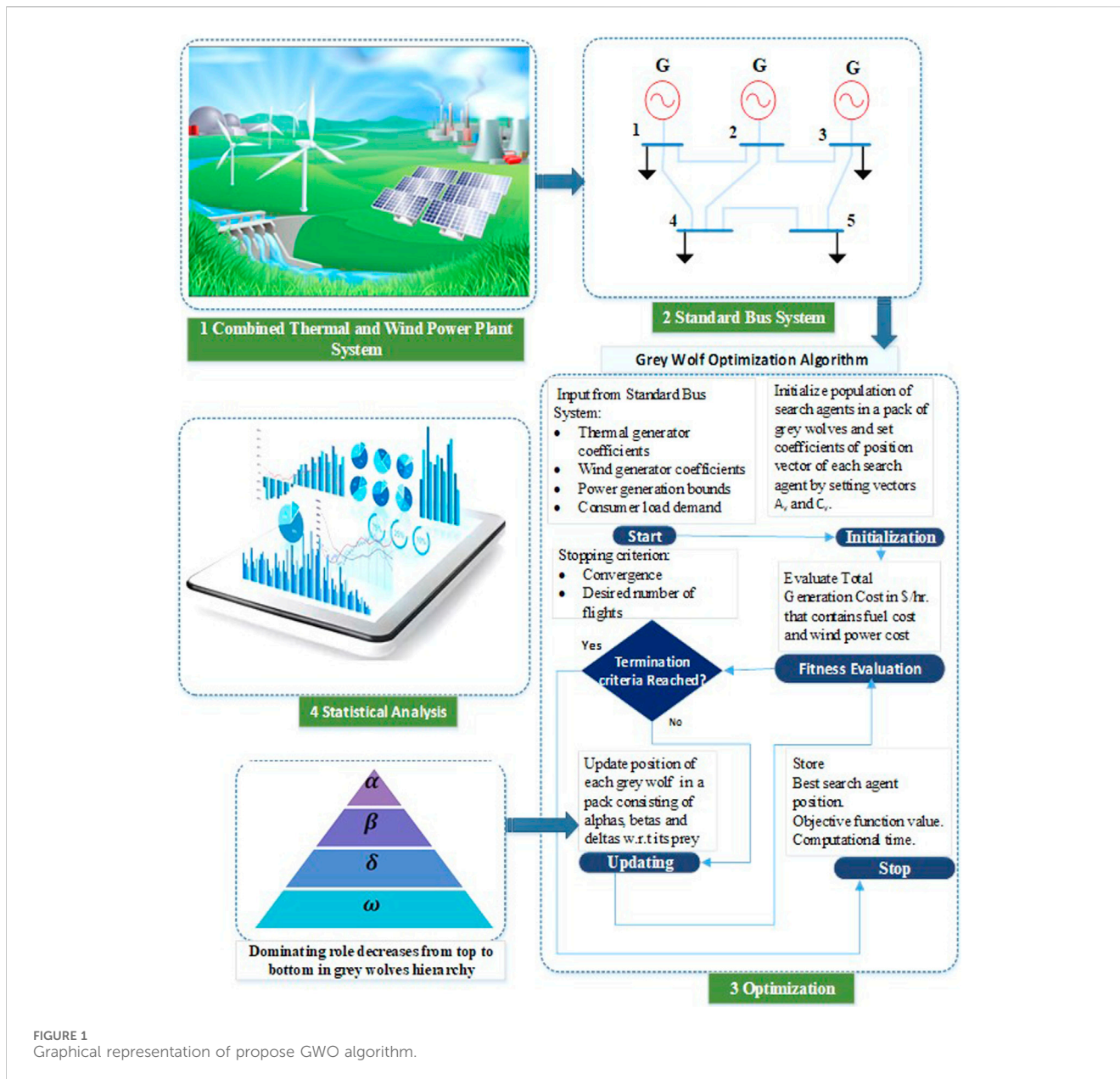
FIGURE 1
Graphical representation of propose GWO algorithm.

alphas die or get too old. Third in line after alphas and betas are delta wolves. Delta follows the command and instructions laid down by alphas and betas. Caretakers, hunters, scouts, elders and sentinels belong to this category. Caretakers take care of weak and wounded wolves whereas scouts keep an eagle eye on all boundaries and generate an alert in case of any danger. Sentinels make sure the safety of entire pack. Fourth in line and bottom of hierarchy comes omega wolves. Omegas has to follow all commands and instructions by all dominating wolves. They usually receive food and all other incentives in last. Among all social activities, hunting is the most important and interesting activity of grey wolves. Keeping in mind the hunting behavior of grey wolves, GWO algorithm is implemented in which initial population of grey wolves is generated and these wolves move in multi-dimensional search space in search of prey. The position

vectors of these search agents i-e grey wolves are considered to be the problem's variables whereas the distance between search agent and its prey is considered to be the fitness value of required objective function. In GWO algorithm each search agent moves in hyper dimensional place and updates its position with respect to its prey over the course of its iterations. The remaining search agents down the hierarchy update their positions with reference to the best individual search agents obtained. The main aim of GWO algorithm is to find the shortest possible path between search agents and prey. Hunting process mainly follows to track, chase and approach prey. Once approach the prey, encircle and start harassment the prey till it gets stationary and finally attacking the prey. GWO mimics the hunting mechanism by mathematical model for searching, approaching, encircling and attacking the prey.

TABLE 1 Comparison of variants of GWO algorithm for case study 1.

Methodology	Search agents' number	Time (sec)	Fuel cost ($/hr.)
GWO-1	500	17.41	123135.1420
GWO-2	1000	77.29	122610.4835
GWO-3	1500	102.52	122455.3325
GWO-4	2000	242.34	122034.4184
GWO-5	2500	170.12	122044.6518
GWO-6	3000	433.80	122300.5862
GWO-7	3500	120.84	122183.2661
GWO-8	4000	578.98	121979.8310
GWO-9	4,500	229.64	122048.0780
GWO-10	5000	472.74	122064.5881

FIGURE 2
Fitness curve of best variant GWO-8 for case study 1.
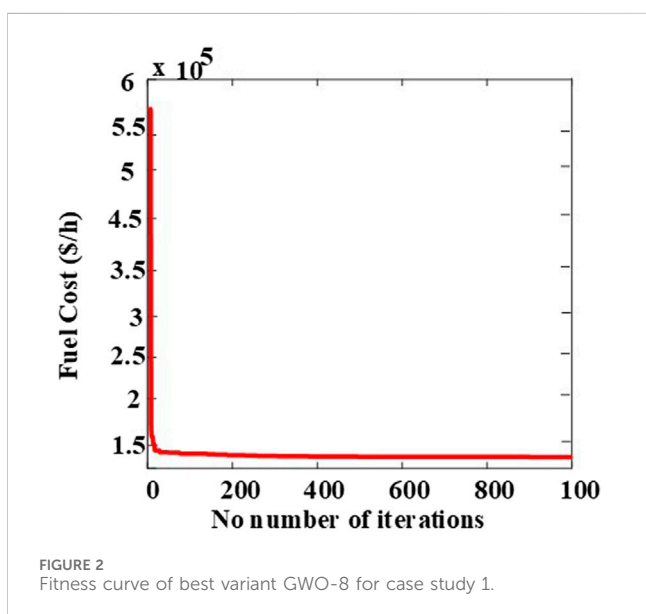
3.2 Exploration phase

In designing the mathematical model for GWO algorithm, the fittest candidates for required solutions are considered as alphas. The second and third best candidates in terms of required solutions considered are betas and deltas respectively. All three candidates guide and assist the hunting mechanism of GWO algorithm. The lowest candidate considered is omega and is compelled to follow alphas, betas and deltas. While exploring the search space, the search agents diverge from one another and readjust their position vectors in hyper dimensional search space while searching for the prey. Coefficient vector A_v provides different random generated values that compel search agents to diverge from the position of prey. While vector C_v provides random generated weights.

Exploration of search space by vectors A_v and C_v make sure the global optimum solutions by GWO algorithm and are mathematically expressed as shown in Eqs 16, 17.

$$\vec{A}_V = 2 \times \vec{p}_1 \times \vec{c}_1 - \vec{p}_1. \tag{16}$$

$$\vec{C}_V = 2 \times \vec{c}_2 \tag{17}$$

Component P_1 of coefficient vector A_v linearly decreases from 2 to 0 during successive iteration whereas C_1 and C_2 being random vectors in the range of 0–1.

3.2.1 Prey encircling phase

Once the prey is approached by search agents during exploration, they start encircling the prey. The best search agents in terms of positions are alphas, betas and gammas while rest of search agents in a pack update their positions with respect to the positions of best search agents obtained so far. The following Eqs 18, 19 has been proposed tomimic the encircling behavior of search agents round the prey.

$$\vec{D}_s = abs\left(\vec{C}_v \times \vec{X}_{prey}(n) - \vec{X}_{wolf}(n)\right). \tag{18}$$

$$\vec{X}_{wolf}(n+1) = \vec{X}_{prey}(n) - \vec{A}_v \times \vec{D}_s \tag{19}$$

D_s is linear distance between search agent and prey and indicates the fitness value of each search agent during the course of iteration. Lesser the distance between search agent and the prey more is the fitness value and *vice versa*. X_{prey} and X_{wolf} are position vectors for prey and search agents respectively.

3.3 Hunting mechanism

The search agents have the potential to track the location of prey and once approached it encircle the prey. Alphas for the instant are best search agents and leads the hunting process while rest of search agents in a pack update their positions with respect

TABLE 2 Statistical results for execution time and fuel generation cost for case study 1.

Variants	Mean		STD	
	Time (sec)	Fuel cost ($/hr.)	Time (sec)	Fuel cost ($/hr.)
GWO-1	17.23	124150	0.12	546.7175
GWO-2	124.34	123630	55.90	598.3160
GWO-3	164.10	123370	66.49	446.4370
GWO-4	223.29	123070	78.10	430.9066
GWO-5	271.01	123020	84.16	395.1835
GWO-6	287.06	123020	93.58	442.9326
GWO-7	121.20	122930	0.64	404.4325
GWO-8	378.55	122780	131.57	402.4765
GWO-9	397.30	122740	143.58	344.7325
GWO-10	411.54	122760	148.71	389.6495

FIGURE 3
Independent runs and histogram observations of variant GWO-8 for case study 1.
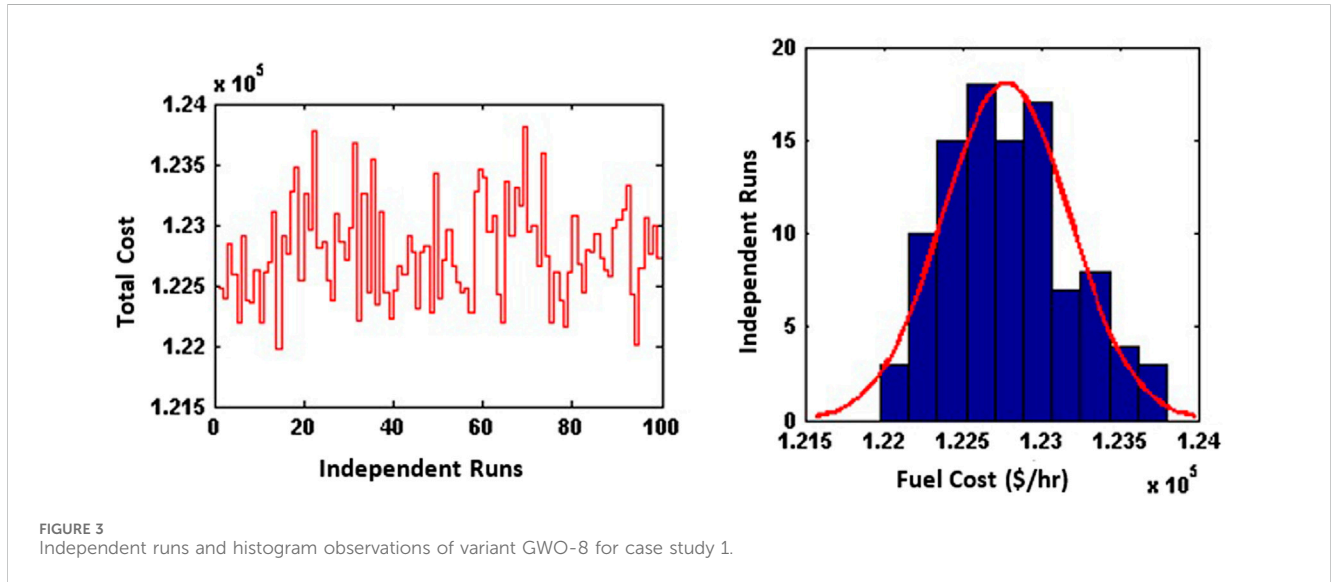
to alphas. Due to diverged search space, we are not sure about optimum location of prey, we therefore consider the positions of alphas, betas and gammas as best solutions and rest of search agents update their positions accordingly. Following formulas regarding the subject matter has been proposed as mentioned in Eqs 20–27.

$$\vec{D}_{s\alpha} = abs\big(\vec{C}_{v1} \times \vec{X}_{prey}(n) - \vec{X}_{wolf,\alpha}(n)\big) \tag{20}$$

$$\vec{D}_{s\beta} = abs\big(\vec{C}_{v2} \times \vec{X}_{prey}(n) - \vec{X}_{wolf,\beta}(n)\big) \tag{21}$$

$$\vec{D}_{s\delta} = abs\big(\vec{C}_{v3} \times \vec{X}_{prey}(n) - \vec{X}_{wolf,\delta}(n)\big) \tag{22}$$

$$\vec{X}_{wolf,\alpha}(n+1) = \vec{X}_{prey}(n) - \vec{A}_{v1} \times \vec{D}_{s\alpha} \tag{23}$$

$$\vec{X}_{wolf,\beta}(n+1) = \vec{X}_{prey}(n) - \vec{A}_{v2} \times \vec{D}_{s\beta} \tag{24}$$

$$\vec{X}_{wolf,\delta}(n+1) = \vec{X}_{prey}(n) - \vec{A}_{v3} \times \vec{D}_{s\delta} \tag{25}$$

$$\vec{X}_{wolf}(n+1) = \frac{\vec{X}_{wolf,\alpha}(n+1) + \vec{X}_{wolf,\beta}(n+1) + \vec{X}_{wolf,\delta}(n+1)}{3} \tag{26}$$

3.4 Exploitation phase

Hunting mechanism led by search agents is compiled by attacking the prey when it comes in stationary position. In exploitation phase the value of component P_1 of coefficient vector A_v is linearly decreased from 2 to 0 over the course of iteration. The decrease in P_1 is hence set responsible and set fluctuation range for A_v. This decrement makes sure that next position for search agent can be anywhere between the position of search agent and position of prey for random values of A_v in the range −1 to 1. Exploration takes place for values of A_v >1 and search

TABLE 3 Comparison of hybridized variants of GWO algorithm for case study 1.

Methodology	Search agents No	Including VPLE			
		Time	Iterations	FC	Fuel cost ($/hr.)
GWO-IPA-1	500	1.10	107	8879	121593.1550
GWO-IPA-2	1000	2.24	232	19156	121600.6300
GWO-IPA-3	1500	2.21	210	17369	121641.2474
GWO-IPA-4	2000	1.21	97	8152	121490.9526
GWO IPA-5	2500	1.64	129	10803	121451.9279
GWO-IPA-6	3000	1.34	126	10463	121456.4441
GWO-IPA-7	3500	1.45	146	12101	121426.8340
GWO-IPA-8	4000	1.02	87	7294	121452.9140
GWO-IPA-9	4500	0.97	87	7265	121468.7313
GWO-IPA-10	5000	1.05	97	8067	121448.1173
GWO-SQP-1	500	0.90	128	10772	121805.6164
GWO-SQP-2	1000	0.83	115	9704	121586.7937
GWO-SQP-3	1500	0.85	115	9856	121681.5235
GWO-SQP-4	2000	1.13	148	12408	121533.5530
GWO-SQP-5	2500	0.78	97	8269	121521.5972
GWO-SQP-6	3000	0.78	98	8236	121534.8218
GWO-SQP-7	3500	1.01	132	11040	121548.9509
GWO-SQP-8	4000	0.95	127	10626	121551.3529
GWO-SQP-9	4500	1.08	113	9465	121777.5099
GWO-SQP-10	5000	0.91	103	8697	121448.6012
GWO-ASA-1	500	4.38	726	30666	121578.9584
GWO-ASA-2	1000	7.59	1,000	82288	121674.7828
GWO-ASA-3	1500	5.52	662	54605	121568.0814
GWO-ASA-4	2000	1.94	242	19845	121637.3382
GWO-ASA-5	2500	1.20	152	12739	121617.7429
GWO-ASA-6	3000	1.18	140	11703	121591.5375
GWO-ASA-7	3500	1.51	194	16618	121647.9019
GWO-ASA-8	4000	1.92	231	19892	121498.2729
GWO-ASA-9	4500	2.45	315	26083	121649.2449
GWO-ASA-10	5000	1.49	185	15343	121765.0747

agents diverge from its prey whereas exploitation takes place for values of $A_v < 1$ and search agents are forced to converge towards the prey and attack them.

Summary of GWO algorithm is presented below.

- Set initial population of search agents i-e wolves. Population size is set by the number of wolves. Each wolf is considered as a candidate solution to the given problem and problem variables are defined by the position vector of each search agent in one

dimensional, two dimensional and higher dimensional search space.
- For each search agent in initial generated population, set position vectors by assigning lower and upper bounds and also set maximum number of iterations as stopping criteria.
- The fitness value of each search agent is evaluated by passing each agent from objective function and its fitness value is evaluated based on the distance between search agent and prey. The best fitness of each search agent is categorized in order of alpha, beta and gamma.

TABLE 4 Comparison of proposed hybrid GWO algorithm for case study 1.

Algorithm	Fuel cost ($/hr.)	Algorithm	Fuel cost ($/hr.)	Algorithm	Fuel cost ($/hr.)
GA-ASA-1 [34]	122,749	EP-SQP [35]	122324	GA-PS-SQP [42]	121458.14
GA-ASA-2 [34]	122,719	NPSO- RLS [36]	123094.98	QPSO [43]	121448.21
GA-ASA-3 [34]	122,683	EP-SQP [37]	122324	BBO [44]	121426.953
GA-ASA-4 [34]	122,369	PSO-LRS [38]	122035.7946	SA-PSO [45]	121430.00
GA-ASA-5 [34]	122,353	NPSO [38]	121704.7391	IGAMU [46]	121819.25
GA-ASA-6 [34]	122,175	NPSO-LRS [38]	121664.4308	ESO [47]	121630.96
GA-ASA-7 [34]	123,062	CBPSO-RVM [39]	121555.32	MHSA [48]	121690.271
GA-ASA-8 [34]	122,796	ACO [40]	121532.41	MFO-IPA-7 [49]	121998.6318]
GA-ASA-9 [34]	122,646	SOH-PSO [41]	121501.14	GWO-IPA-7	121426.8340
EP-SQP [35]	122324	EP-SQP [35]	122324	EP-SQP [35]	122324
NPSO- RLS [36]	123094.98	NPSO- RLS [36]	123094.98	NPSO- RLS [36]	123094.98

- Each search agent updates its position over the course of successive iteration.
- GWO algorithm is terminated once pre-defined tolerance or maximum number of iterations are reached.

```
· Set initial population of search agents.
· Set position vector of each search agents by setting $\vec{p}_1$,
  $\vec{A}_V$ and $\vec{C}_v$.
· Evaluate the fitness level of each search agent by
  passing through desired objective function.
· $\vec{X}_{wolf,\alpha}$ =Best fitness evaluation is of search agent alpha.
· $\vec{X}_{wolf,\beta}$ =Second Best fitness evaluation is of
  search agent beta.
· $\vec{X}_{wolf,\delta}$ = Third Best fitness evaluation is of search
  agent delta.
· while (n<iterations)
·        for each search agent update the position using
         equation (26)
·        end for loop
· Update position vector of each search agent by updating
  values for $\vec{p}_1$, $\vec{A}_V$ and $\vec{C}_v$.
· Evaluate fitness value of all search agents
         $\vec{X}_{wolf,\alpha}, \vec{X}_{wolf,\beta}$ and $\vec{X}_{wolf,\delta}$
· Update
· n=n+1
· end while loop
```

Algorithm 1. GWO Algorithm.

3.5 Application of GWO to solve ELD-VPLE and ELD-VPLE-SW problems

Step 1: Initializing population of grey wolves.

Random initial population of search agents, i.e., grey wolves consisting of alpha, beta and gamma wolves is generated. Each search agent of initial population provides feasible solutions to constrained optimization problem of ELD. The position vector of each search agent represents active power generation in KW or MW within its upper and lower bound of each power generating unit. The position of each search agent is set by the initialization of sets of controlled variables in terms of active power generation. Initial population of grey wolves in terms of active power generation of each power generating unit for ELD problem containing SW is presented below.

$$P = \begin{pmatrix} P_1^1, P_2^1, \cdots\cdots P_m^1, W.P_1^1, W.P_2^1, \cdots\cdots\cdots W.P_n^1 \\ P_1^2, P_2^2, \cdots\cdots P_m^2, W.P_1^2, W.P_2^2, \cdots\cdots\cdots W.P_n^2 \\ P_1^3, P_2^3, \cdots\cdots P_m^3, W.P_1^3, W.P_2^3, \cdots\cdots\cdots W.P_n^3 \\ \vdots \\ \vdots \\ \vdots \\ P_1^{Z-1}, P_2^{Z-1}, \cdots P_m^{Z-1}, W.P_1^{Z-1}, W.P_2^{Z-1}, \cdots W.P_n^{Z-1} \\ P_1^Z, P_2^Z, \cdots P_m^Z, W.P_1^Z, W.P_2^Z, \cdots\cdots\cdots W.P_n^Z \end{pmatrix} \quad (27)$$

Where "m" and "n" are total numbers of thermal power generating units and wind power generating units respectively whereas "z" represents population size of grey wolves.

Step 2: Evaluating fitness level of grey wolves.

After the generation of initial population of grey wolves, the fitness level of each set of search agents is evaluated based on its fitness value by passing them through required objective functions in Eq 2 and Eq. 3. The fitness value of each search agent reflects how far is its position from prey in terms of generation cost in $/hr.

Step 3: Sorting in terms of its fitness levels.

The fitness value of each search agent reflecting total generation cost in $/hr. is sorted and is placed in order such that alpha wolves having the best fitness value while second and third best fitness values are for beta and gamma wolves respectively.

TABLE 5 Statistical results of hybridized variants of GWO algorithm for case study 1.

Methodology	Search agents' number	Mean				STD			
		Time (sec)	Iterations	F.C	Fuel cost ($/hr.)	Time (sec)	Iterations	F.C	Fuel cost ($/hr.)
GWO-IPA-1	500	1.86	174	14405	122480.9528	0.69	65	5297	454.6729
GWO-IPA-2	1000	1.73	164	13559	122209.2272	0.67	65	5303	407.6212
GWO-IPA-3	1500	1.57	146	12151	122084.3843	0.45	43	3549	333.7528
GWO-IPA-4	2000	1.48	136	11325	121944.3904	0.47	42	3425	306.4992
GWO-IPA-5	2500	1.58	147	12227	121862.0788	0.48	43	3539	269.4663
GWO-IPA-6	3000	1.49	138	11421	121902.4361	0.47	45	3665	292.4632
GWO-IPA-7	3500	1.44	136	11300	121878.6558	0.44	40	3316	292.2390
GWO-IPA-8	4000	1.43	132	10987	121840.3937	0.39	38	3091	261.0680
GWO-IPA-9	4500	1.49	137	11383	121836.4156	0.51	45	3669	246.7808
GWO-IPA-10	5000	1.35	127	10524	121862.6348	0.38	34	2,826	233.4188
GWO-SQP-1	500	0.99	71	8485	123480.0961	3.95	149	28710	883.9448
GWO-SQP-2	1000	0.50	43	4,612	123194.9258	1.72	81	14181	791.2862
GWO-SQP-3	1500	0.89	60	7617	122956.3071	3.80	147	28999	640.4511
GWO-SQP-4	2000	0.31	25	2,734	122861.3539	1.05	55	7975	553.1321
GWO-SQP-5	2500	0.26	27	2,460	122771.4704	0.38	51	4,213	617.2696
GWO-SQP-6	3000	0.20	21	1880	122836.9971	0.32	43	3578	602.8919
GWO-SQP-7	3500	0.20	20	1867	122775.3941	0.36	49	4,034	488.6978
GWO-SQP-8	4000	0.54	32	4,252	122584.0724	3.26	107	22426	496.3900
GWO -SQP-9	4500	0.14	12	1,122	122651.9729	0.24	31	2,568	384.4202
GWO -SQP-10	5000	0.25	17	2038	122649.9914	0.99	44	7134	448.6538
GWO-ASA-1	500	2.62	418	17965	122517.5889	1.67	245	10461	449.8072
GWO-ASA-2	1000	2.42	274	23079	129899.3058	1.83	214	18492	12067.8520
GWO-ASA-3	1500	2.50	280	23563	128054.4276	1.77	205	17747	10557.9744
GWO-ASA-4	2000	2.16	238	19933	131523.8284	1.63	183	15176	12949.7432
GWO-ASA-5	2500	2.24	247	20658	132209.2469	1.83	202	16755	13759.8316
GWO-ASA-6	3000	2.10	230	19363	131525.7229	1.83	200	17361	12536.3359
GWO-ASA-7	3500	2.32	254	21466	133686.6134	1.84	202	17470	15024.7445
GWO-ASA-8	4000	2.54	280	23353	129529.7149	1.89	218	18207	12022.2646
GWO-ASA-9	4500	2.34	258	22002	133765.3417	2.03	233	20610	14027.2637
GWO-ASA-10	5000	2.26	247	20876	131707.2241	1.84	201	17500	13954.7923

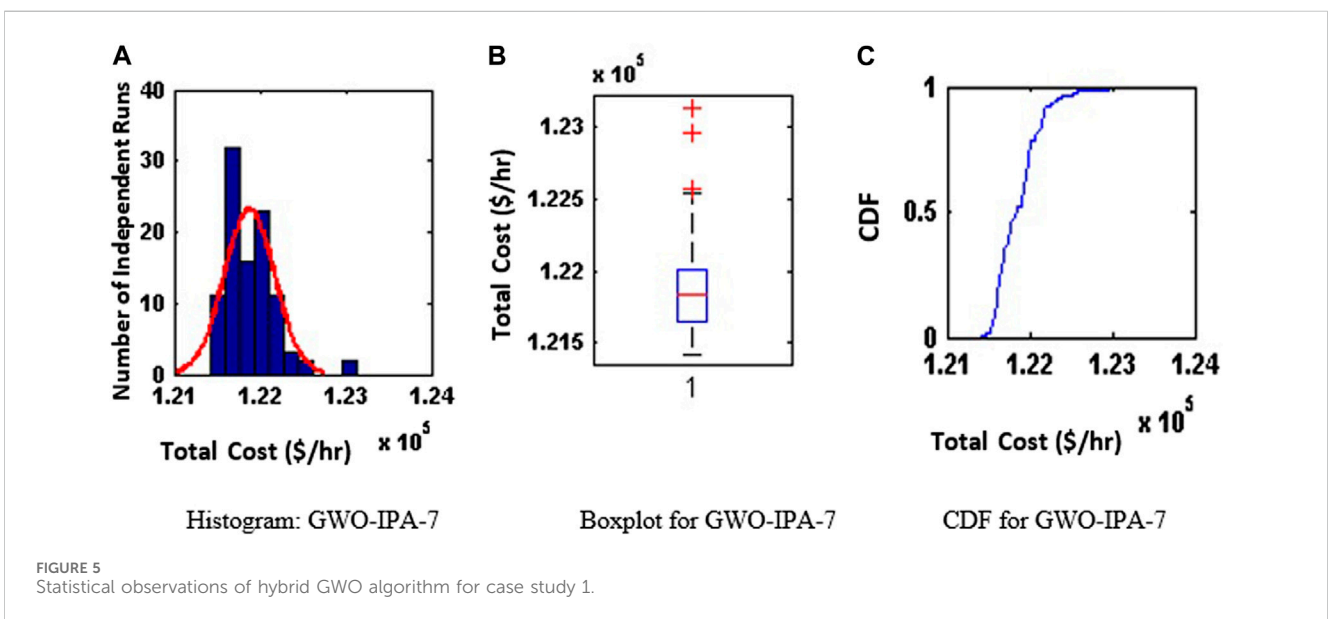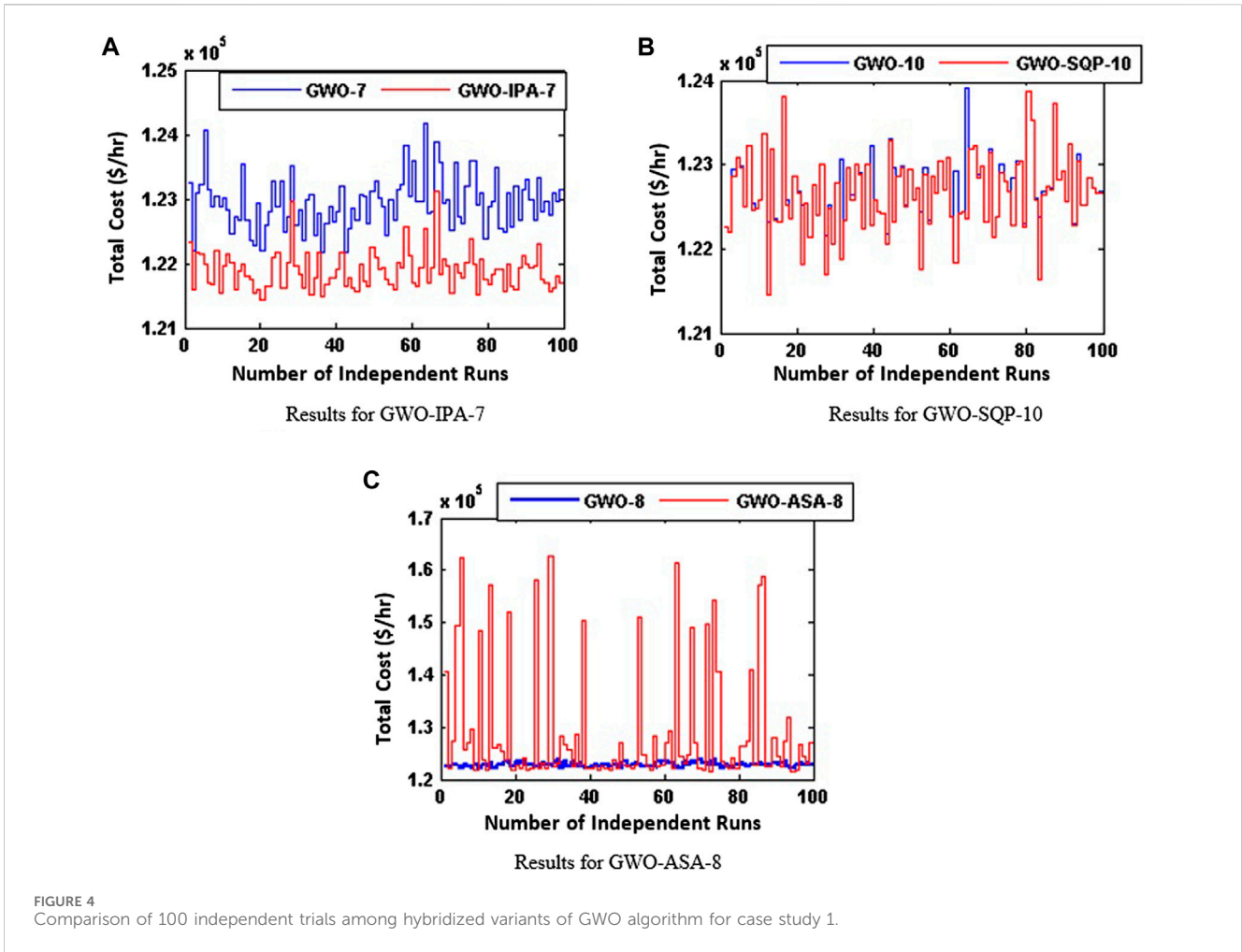**Step 4:** Position updating mechanism.

During the course of iteration in GWO algorithm, each search agent is motivated to update its current position with respect to prey based upon searching, prey encircling followed by hunting and attacking. In this regard different positions adopted by each search agent represents the possible controlled variables of real power output in MW for each power generating unit to reduce total generation cost in dollars per hour.
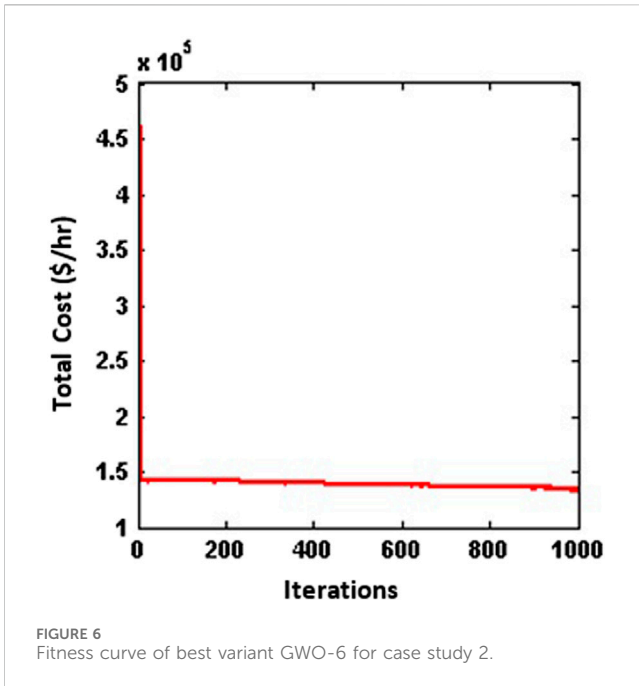
Step 5: Checking inequality constraint violation.

If the position of any search agent violates its limits, bring back to its limits. These limits reflect the minimum and maximum power generation limits for each power generating unit.

Step 6: Stopping criteria.

If there is no comprehensive change of fitness. or predefined number of iterations have reached, the execution of GWO algorithm is stopped else return to Step 2.

FIGURE 4
Comparison of 100 independent trials among hybridized variants of GWO algorithm for case study 1.

FIGURE 5
Statistical observations of hybrid GWO algorithm for case study 1.

FIGURE 6
Fitness curve of best variant GWO-6 for case study 2.

4 Case studies and simulation results

In order to show the effectiveness of nature-inspired computational paradigm via grey wolf optimization (GWO) algorithm, two case studies dependents upon ELD-VPLE and ELD-VPLE-SW have been proposed. For rapid local convergence the optimized results of GWO algorithm have been hybridized with local search-based techniques of SQP, ASA, and IPA.

4.1 Case study 1

This case study consists of 40 thermal power generating units whose fuel cost coefficients have been taken from (Morshed and Asgharpour, 2014) and power demand considered is 10,500 MW. The physical phenomenon reflecting the realistic behavior of power system dynamics has been included by considering VPLE. In case study 1 GWO is applied through variants that ranges from 500 search agents' number to 5000. The randomness of the optimized simulation results of GWO algorithm cannot be ignored owing to its stochastically varying behavior. In this regard 100 independent trials for each variant of GWO algorithm with 1,000 iterations have been applied to closely monitor the probability of deviations in optimized results. The best fuel cost value in $/hr. for each variant of GWO algorithm among 100 independent trials along with its execution time is tabulated in Table 1. Among all ten variants of GWO algorithm, comparatively GWO-8 showed better convergence for minimum fuel cost of 121979.8310 $/hr. with execution time of 578.98 s. The learning curve for the best variant recorded is shown in Figure 2, while the values for deciding variables in terms of active power generations

output in MW for GWO-8 variant is shown in Supplementary Appendix Table SA1 table A1 of appendix.

Inputs: The best individual search agents sorted by GWO Algorithm for 40 generating units for ELD-VPLE and ELD-SW. Mathematically can be represented as follows:

$$P_{GWO} = \begin{bmatrix} (P_1, P_2, P_3, \ldots, P_m) \\ (P_1, P_2, P_3, \ldots, P_m, W.P_1, W.P_2, \ldots W.P_n) \end{bmatrix}$$

Output: The best individual search agents sorted by GWO for 40 generating units are further refined by local search techniques.

$$P_{GWO-SQP} = \begin{bmatrix} (P_1, P_2, P_3, \ldots, P_m) \\ (P_1, P_2, P_3, \ldots, P_m, W.P_1, W.P_2, \ldots W.P_n) \end{bmatrix}$$

$$P_{GWO-ASA} = \begin{bmatrix} (P_1, P_2, P_3, \ldots, P_m) \\ (P_1, P_2, P_3, \ldots, P_m, W.P_1, W.P_2, \ldots W.P_n) \end{bmatrix}$$

$$P_{GWO-IPA} = \begin{bmatrix} (P_1, P_2, P_3, \ldots, P_m) \\ (P_1, P_2, P_3, \ldots, P_m, W.P_1, W.P_2, \ldots W.P_n) \end{bmatrix}$$

Initialization: Parameters, assignments and constraints of local search (SQP, ASA and IPA) techniques are initialized.

Termination: Stopping criteria for all local search techniques are set as follows:
- Max Function Evaluations=300000;
- Max Iterations=1000;
- Tolerance Function=1e-12;
- Tolerance X=1e-10;
- Algorithms
    o 'interior-point',
    o 'active-set',
    o 'SQP';
- Finite Difference Type='central';
- Tolerance Con=1e-12;

While (Stopping criteria satisfied) **do**

Cost Calculation: Calculate fuel cost for ELD-WV function using equation 2 and total cost of integrated stochastic wind for ELD-VPLE-SW using equation 12

Stoppage: Exit from the main loop if all stopping criteria are met else continue.

End:

Algorithm2. Local Search Algorithms (SQP, ASA and IPA).

Furthermore, the statistical results for execution time in seconds and fuel generation cost among 100 independent trials for each variant are placed in Table 2. The 100 independent trials for best variant of GWO and histogram are shown in Figure 3. The mean value of fuel cost goes on decreasing while computational complexity goes on increasing with each successive set of increased search agent's number. Moreover, the standard deviation reflects dynamics of search space increases by increasing search agent's number.

The optimized results of each variant of GWO were given to local based search techniques of SQP, ASA and IPA for further refinement. Table 3 consists of the best simulation results among 100 independent trials for each hybridized scheme of GWO algorithm in terms of computational execution, function counts
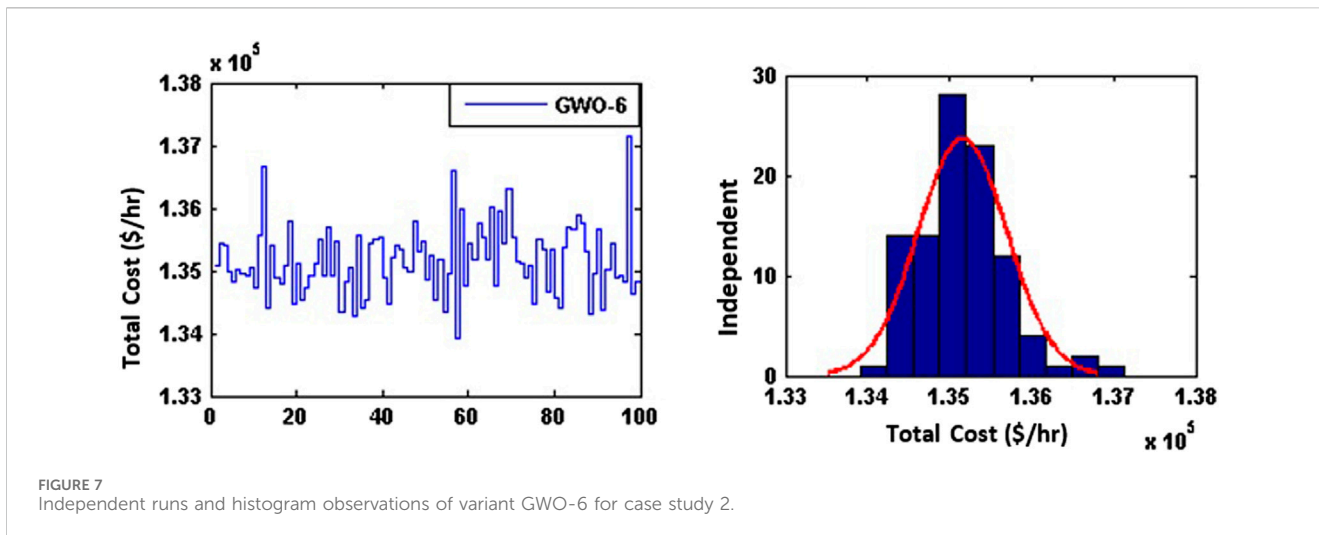
FIGURE 7
Independent runs and histogram observations of variant GWO-6 for case study 2.

TABLE 6 Comparison of variants of GWO algorithm for case study 2.

Methodology	Search agents no	Time (sec)	Fuel cost ($/hr.)	Wind power cost ($/hr.)	Total cost ($/hr.)
GWO-1	500	13.97	118553.4724	16629.3891	135184.8935
GWO-2	1000	30.11	117920.6849	16682.9697	134608.9942
GWO-3	1500	43.31	117776.2226	16698.4225	134481.9588
GWO-4	2000	60.33	117706.0629	16621.4011	134329.6809
GWO-5	2500	79.38	117589.1806	16621.6584	134217.8542
GWO-6	3000	91.94	117293.6596	16613.5577	133910.1427
GWO-7	3500	103.63	117442.6352	16644.0790	134087.8705
GWO-8	4000	121.38	117503.3867	16618.8767	134122.3280

TABLE 7 Statistical results for execution time and total generation cost for case study 2.

Methodology	Search agents no	Mean		STD	
		Time (sec)	Total cost ($/hr.)	Time (sec)	Total cost ($/hr.)
GWO-1	500	14.49	136299.4133	0.39	615.5426
GWO-2	1000	29.37	135704.2748	0.54	483.2496
GWO-3	1500	43.83	135487.696	0.72	518.3162
GWO-4	2000	58.93	135237.4796	1.25	487.0783
GWO-5	2500	76.00	135169.0305	1.57	457.3314
GWO-6	3000	90.32	135157.1608	1.64	545.4567
GWO-7	3500	105.21	134892.5012	3.06	403.5863
GWO-8	4000	137.00	134833.5954	5.07	406.1086

(FC), iterations and fuel generation cost. The stopping criteria for each local based search techniques are presented in Algorithm 2. Among hybridized variants of GWO algorithm with IPA, the prime optimized outcomes with regard to fuel generation cost of 121426.8340 $/hr. were recorded for GWO-IPA-7 while in case

of SQP and ASA the prime optimized outcomes with regard to fuel generation cost of 121448.6012 $/hr. and 121498.2729 $/hr. were recorded for GWO-SQP-10 and GWO-ASA-8 respectively. The hybridized scheme of GWO algorithm with IPA gave minimum fuel cost of 121426.8340 $/hr. compared to SQP and ASA

TABLE 8 Comparison of hybridized variants of GWO algorithm for case study 2.

Methodology	Search agents no	Time (sec)	Iterations no	F.C	Fuel cost ($/hr.)	Wind power cost ($/hr.)	Total cost ($/hr.)
GWO-IPA-1	500	3.22	155	12851	117063.12200	16609.44323	133672.5659
GWO-IPA-2	1000	35.00	221	18361	117070.88545	16609.44323	133680.3289
GWO-IPA-3	1500	6.27	109	9105	116848.25746	16609.44323	133457.7020
GWO-IPA-4	2000	11.41	135	11189	116882.88438	16609.44323	133492.3302
GWO-IPA-5	2500	4.81	103	8601	116845.96990	16609.44323	133455.4127
GWO-IPA-6	3000	5.83	137	11385	116880.50953	16609.44323	133489.9531
GWO-IPA-7	3500	4.86	121	10003	116790.84878	16609.44323	133400.2927
GWO-IPA-8	4000	6.10	129	10739	116778.50040	16609.44323	133387.9413
GWO-SQP-1	500	5.47	139	11683	116985.59300	16609.44323	133595.0361
GWO-SQP-2	1000	7.02	153	13058	117028.76016	16609.44323	133638.2073
GWO-SQP-3	1500	7.07	138	11612	116904.77801	16609.44323	133514.2202
GWO-SQP-4	2000	10.61	205	17090	117044.36284	16609.44323	133653.8055
GWO-SQP-5	2500	5.04	141	11880	116866.78669	16609.44323	133476.2280
GWO-SQP-6	3000	4.66	130	10954	117146.27217	16609.44323	133755.7130
GWO-SQP-7	3500	4.20	116	9742	116888.98573	16609.44323	133498.4302
GWO-SQP-8	4000	4.18	106	8952	116948.88903	16609.44323	133558.3302
GWO-ASA-1	500	30.57	416	34385	117190.34985	16609.44323	133799.7932
GWO-ASA-2	1000	60.91	608	50646	117121.19443	16609.44323	133730.6371
GWO-ASA-3	1500	13.849	349	29440	117072.82717	16609.44323	133682.2681
GWO-ASA-4	2000	23.14	209	17796	116978.28437	16609.44323	133587.7278
GWO-ASA-5	2500	71.37	642	52888	116964.04330	16609.44323	133573.4870
GWO-ASA-6	3000	26.11	207	17464	116958.03777	16609.44323	133567.4827
GWO-ASA-7	3500	16.17	310	25947	116955.04867	16609.44323	133564.4956
GWO-ASA-8	4000	30.64	359	30746	116792.10294	16609.44323	133401.5454

algorithms. The values for deciding variables i-e active power generation outputs in MW in case of GWO-IPA-7 variant are shown in Supplementary Appendix Table SA2.

In case of ELD problem with VPLE, outcomes were collate with benchmark solvers that includes GA-ASA-1 to GA-ASA-9 (Jamal and MenKhanRaja, 2019), EP-SQP (Attaviriyanupap et al., 2002), NPSO-RLS (Selvakumar and Thanushkodi, 2007a), EP-SQP (Chiang, 2007a), PSO-LRS (Kuo, 2008), NPSO (Kuo, 2008), NPSO-LRS (Kuo, 2008), CBPSO-RVM (Selvakumar and Thanushkodi, 2007b), ACO (Pereira-Neto et al., 2005a), SOH-PSO (Vlachogiannis and Lee, 2009), GA-PS-SQP (Chiang, 2007b), QPSO (Lu et al., 2010), BBO (Liu and Xu, 2010b), SA-PSO (Panigrahi et al., 2008), IGAMU (Hosseinnezhad and Babaei, 2013), ESO (Pereira-Neto et al., 2005b), MHSA (Arul et al., 2013), MFO-8 (Khan et al., 2021), MFO-IPA-7 (Khan et al., 2021), MFO-SQP-6 (Khan et al., 2021) and MFO-ASA-2 (Khan et al., 2021) in Table 4. Among reported results the best results were found for BBO (Liu and Xu, 2010b)

while the proposed GWO-IPA-7 performed even better in terms of fuel cost giving value of 121426.8340 $/hr. compared to that of BBO of 121426.953 $/hr.

The statistical results for all hybridized schemes of GWO algorithm based on 100 independent trials in terms of mean and standard deviations for execution time, iterations, FC and fuel cost are tabulated in Table 5. In case of GWO-IPA-7 the values of mean and standard deviations for execution time, iterations, FC and fuel cost recorded are 1.44 ± 0.44, 136 ± 40, 11300 ± 3316 and 121878.6558 ± 292.2390 respectively Simulation results in terms of fuel cost values for best recorded hybridized variants of GWO algorithm i-e., GWO-IPA-7, GWO-SQP-10 and GWO-ASA-8 for 100 independent trials are shown in Figure 4. Furthermore, the statistical performance indices among best variants in case of hybridized GWO algorithm with local search algorithm of IPA was aided with histogram, boxplot and cumulative density function (CDF) based analysis presented in Figure 5. Histogram based analysis shows that
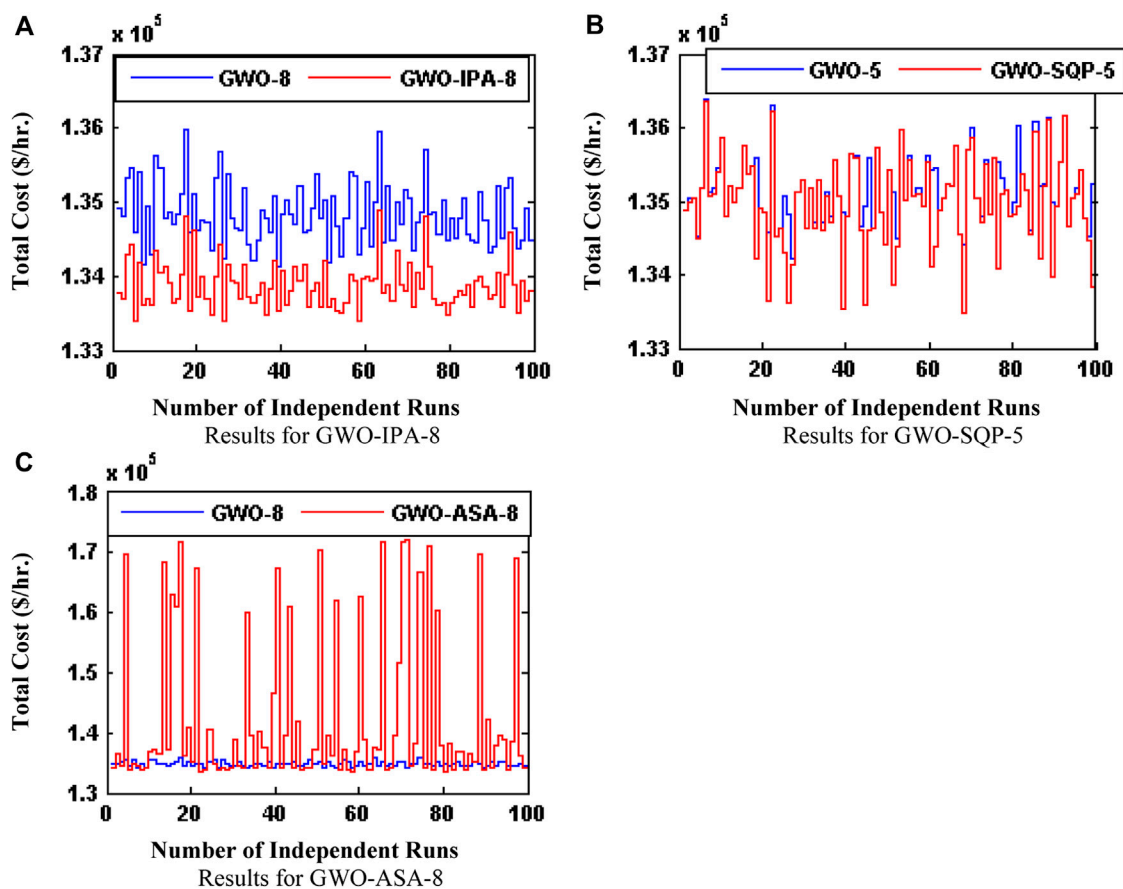
FIGURE 8
Comparison of 100 independent trials among hybridized variants of GWO algorithm for case study 2.

majority of independent runs have occurred around the mean value of Gaussian fit while the mean values tabulated in Table 5 are reflected by the median lines of boxplot. Whereas 70–75 percent results were found accurate as it is well obvious from boxplot analysis.

4.2 Case study 2

A modified case study of ELD-VPLE of 40 generators is considered by taking 37 thermal power generating units of case study 1 and last three units of wind power generating units are considered for case study 2. ELD-VPLE containing SW is incorporated by using system model formulation of Eq. 3. Total generation cost is incorporated using Equation (11). Units' data for thermal and wind power generating units have been taken from (Morshed and Asgharpour, 2014). Hundred independent trials for each variant of GWO algorithm with 1,000 iterations have been applied. The best total cost value in $/hr. along with its fuel cost value, wind power cost and execution time for each variant of GWO algorithm among 100 independent trials is tabulated in Table 6.

Comparatively the pre-eminent simulation outcomes of total cost of 133910.1427 $/hr. were recorded in case of GWO-6 with fuel cost and wind power costs of 117293.6596 and

16613.5577 respectively. The learning curve for GWO-6 is shown in Figure 6, while the values for deciding variables in terms of active power generations output in MW for GWO-6 variant is shown in Supplementary Appendix Table SA3. The 100 independent trials and histogram for best variant of GWO, i.e., GWO-6 are shown in Figure 7. The analysis is further based on statistical results for execution time and fuel cost in terms of mean and standard deviations among 100 independent trials for each variant and are placed in Table 7. The mean value of total cost goes on decreasing while computational complexity goes on increasing with each successive set of increased search agent's number. Moreover, the standard deviation reflects dynamics of search space increases by increasing search agent's number.

Furthermore SQP, ASA and IPA were incorporated with each variant of GWO algorithm i-e. GWO-1 to GWO-8 for refinement of global optimum outcomes of GWO. The best optimized results for each hybridized variant of GWO algorithm among 100 independent trials is presented in Table 8. Algorithm 2 presents stopping criteria for SQP, ASA and IPA. Among hybridized scheme methodology of GWO-IPA-8 gave better convergence result with total cost of 133387.9413 $/hr. having fuel cost of 116778.50040 $/hr. and wind power cost of 16609.44323 $/hr. The 100 independent trials data for each scheme of hybridized GWO variants were analyzed in terms of statistical performance indices. The total

TABLE 9 Statistical results of hybridized variants of GWO algorithm for case study 2.

Methodology	Search agents no	Mean				STD			
		Time (sec)	Iterations no	F.C	Total cost ($/hr.)	Time (sec)	Iterations no	F.C	Total cost ($/hr.)
GWO-IPA-1	500	3.92	178	14815	134621.9385	1.75	67	5526	521.4935
GWO-IPA-2	1000	11.24	159	13178	134319.3752		63	5141	418.3703
GWO-IPA-3	1500	11.22	165	13729	134177.1715	8.81	58	4,717	403.9840
GWO-IPA-4	2000	11.16	159	13216	134055.5508	8.87	49	4,039	353.4225
GWO-IPA-5	2500	10.16	148	12283	133998.6195	8.05	62	5116	347.9615
GWO-IPA-6	3000	9.74	149	12329	134109.9154	6.79	49	4,011	407.5784
GWO-IPA-7	3500	8.76	138	11429	133946.7597	5.50	39	3206	300.1547
GWO-IPA-8	4000	8.62	138	11468	133876.6169	7.12	39	3188	312.8869
GWO-SQP-1	500	2.38	59	5069	135563.8653	4.12	71	5915	974.4272
GWO-SQP-2	1000	1.56	31	2,725	135332.4864	2.24	53	4,431	716.8357
GWO-SQP-3	1500	1.27	32	2,843	135153.0475	1.99	58	4,765	734.6508
GWO-SQP-4	2000	4.47	51	8061	135012.5427	19.50	174	35048	591.9517
GWO-SQP-5	2500	0.93	22	2038	134960.5155	1.54	46	3791	614.5898
GWO-SQP-6	3000	1.81	25	3466	135018.8958	11.13	106	20684	622.9246
GWO-SQP-7	3500	1.09	21	1931	134742.569	1.97	47	3903	533.8159
GWO-SQP-8	4000	0.69	11	1,072	134735.8766	1.11	28	2,346	474.6967
GWO-ASA-1	500	24.56	319	26655	140769.6966	20.40	217	18039	11219.2687
GWO-ASA-2	1000	22.12	312	26163	141804.2457	16.38	231	19432	12697.2654
GWO-ASA-3	1500	23.74	289	24624	140063.1124	18.28	213	18750	10212.9230
GWO-ASA-4	2000	22.30	286	23862	139914.5327	19.19	224	18579	10219.7670
GWO-ASA-5	2500	24.78	275	23148	141871.1348	24.25	210	17735	12296.7052
GWO-ASA-6	3000	23.74	256	21860	140911.3517	19.75	209	19131	10821.2086
GWO-ASA-7	3500	22.56	262	22316	142172.0309	20.68	232	20615	11541.6844
GWO-ASA-8	4000	24.41	264	22263	142423.0414	25.49	198	16655	12750.8630

cost for all hybridized schemes of GWO variants against 100 independent trials are shown in Figure 8, while Table 9 shows the numerical outcomes of statistical performance indices in terms of mean and standard deviations for time, iterations, function count and total cost. The findings for computational time, iterations, function counts and fuel generation cost through mean and standard deviation operators are 8.62 ± 7.12, 138 ± 39, 11468 ± 3188 and 133876.62 ± 312.8869, respectively for GWO-IPA-8. In case of GWO-SQP-5, the values for time, iterations, function count and fuel cost are 0.93 ± 1.54, 22 ± 46, 2038 ± 3791 and 134960.52 ± 614.5898, respectively. Total generation cost based on 100 independent trials in case of each hybridized variant of GWO algorithm was analyzed for statistical observations aided with histogram, boxplot and CDF based studies. These statistical based observation plots are presented in Figure 9. The occurrence

of most of independent trials data is around the mean value of Gaussian fit in histogram based analysis. Table 9 reflects the occurrence of median values closest to the mean values of median lines for boxplots excluding outliers. Reasonable accuracy for 100 independent trials with probability occurrence of more than 0.8 is investigated using CDF plots. The results of the proposed variant of GWO hybrid with SQP, IPA and ASA to solve the ELD problem with VPLE involving SW impact were compared with the state-of-the-art reported solvers including HIC-SQP (Morshed and Asgharpour, 2014), MFO-9 (Khan et al., 2021), MFO-SQP-10 (Khan et al., 2021), MFO-ASA-10 (Khan et al., 2021), MFO-IPA-9 (Khan et al., 2021), PWTED1 (Azizipanah-Abarghooee et al., 2012), DWTED1 (Azizipanah-Abarghooee et al., 2012) and are listed Table 10. Among the reported results, the best was found for MFO-IPA-9 with total cost 133809.3271$/hr. having fuel cost of 117199.8838$/hr. and
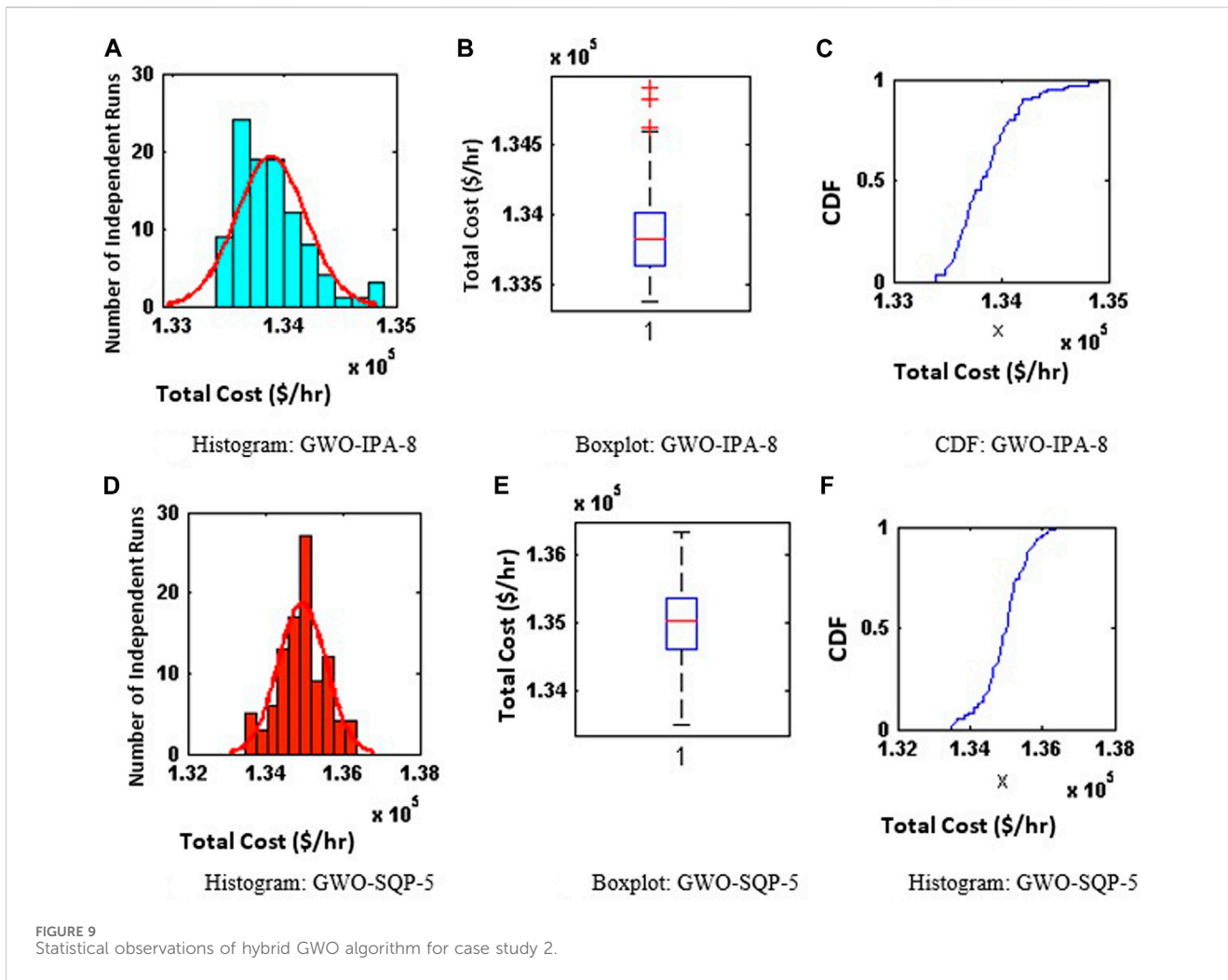
FIGURE 9
Statistical observations of hybrid GWO algorithm for case study 2.

TABLE 10 Comparison of proposed hybrid GWO algorithm for case study 2.

Algorithm	Fuel cost ($/hr.)	Wind power cost ($/hr.)	Total cost ($/hr.)
HIC-SQP (Morshed and Asgharpour, 2014)	119664.5367	16716.8463	136381.3831
MFO-SQP-10 (Khan et al., 2021)	117668.1916	16609.44323	134277.6348
MFO-ASA-10 (Khan et al., 2021)	117739.1102	16609.44323	134348.5534
MFO-IPA-9 (Khan et al., 2021)	117199.8838	16609.44328	133809.3271
PWTED1 (Azizipanah-Abarghooee et al., 2012)	NA	NA	137984.38
DWTED1 (Azizipanah-Abarghooee et al., 2012)	NA	NA	137190.31
Best Compromise (Azizipanah-Abarghooee et al., 2012)	NA	NA	143587.9
GWO-6	117293.6596	16613.5577	133910.1427
GWO-IPA-8	116778.50040	16609.44323	133387.9413
GWO-SQP-5	116866.78669	16609.44323	133476.2280
GWO-ASA-8	116792.10294	16609.44323	133401.5454

wind power cost of 16609.44328$/hr. Among the proposed variants of GWO algorithm, GWO-6 outperformed by optimizing total generation cost to 133910.1427 $/hr. with fuel cost of 117293.6596 $/hr. and wind power cost of 16613.5577 $/hr. Among hybridized schemes of each variant of GWO algorithm with local search-based algorithms, GWO-IPA-8 performed better in terms of total generation cost of 133387.9413 $/hr. having fuel cost of 116778.50040 $/hr. and wind power cost of 16609.44323 $/hr. The second-best results among hybridized schemes were found for GWO-ASA-8 with total generation cost of 133401.5454 $/hr. having fuel cost of 116792.10294 $/hr. and wind power cost of 16609.44323$/hr. followed by GWO-SQP-5 with total generation cost of 133476.2280 $/hr.

5 Conclusion

This work makes a significant contribution to the field of power system optimization by using the hybrid GWO method to solve the challenging ELD problem. Our study's methodology has demonstrated a significant decrease in fuel generating costs and an improvement in the operational efficiency of the power system. The hybrid GWO algorithm has resulted in notable improvements in performance. However, it is critical to identify potential roadblocks and avenues for more research. Concluding remarks are listed as follows.

- Total generation cost of hybrid energy generating units in terms of fuel generation cost and stochastically varying wind power cost is efficiently optimized by exploring and exploiting the searching capabilities of GWO algorithm.
- The effectiveness of proposed GWO algorithm is tested based on different variants. Each set of GWO variant is depending upon the population size of search agents. For further refinement the global outcomes of GWO algorithm are used as starting points for local search-based algorithms of SQP, ASA, and IPA.
- Two case studies involving 40 thermal generators and 3 wind power generators have been considered to show the effectiveness of proposed GWO algorithm.
- For case study 1, GWO-8 variant gave better result for fuel generation cost of 121979.8310 $/hr., while GWO-IPA-7 showed better results of 121426.8340 $/hr.
- For case study 2, GWO-6 variant showed better optimized results for total generation cost of 133910.1427$/hr. with fuel generation cost of 117293.6596 $/hr. and wind power cost of 16613.5577 $/hr. while total generation cost of 133387.9413$/hr. with total generation cost of 116778.50040 $/hr. and wind power cost of 16609.44323 $/hr. were recorded for GWO-IPA-8.
- The performance of proposed case studies was performed based upon 100 independent trials data through statistical, histogram, boxplot and cdf based analysis.

The approach adopted in the present research work may be utilized in the significant areas pertaining to electric power system (Cui et al., 2020; He et al., 2020; Zhou et al., 2020) including integrated hydro-thermal-wind systems (Wang et al., 2019).

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

AW: Conceptualization, Formal Analysis, Methodology, Supervision, Writing–review and editing, Resources. BK: Conceptualization, Formal Analysis, Supervision, Writing–original draft, Writing–review and editing, Resources. TK: Funding acquisition, Software, Writing–original draft, Data curation, Project administration. K-CK: Funding acquisition, Project administration, Supervision, Investigation, Writing–original draft. SR: Funding acquisition, Project administration, Supervision, Conceptualization, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2024.1301700/full#supplementary-material

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