Hybrid Search Optimization for Multiobjective Wind-Thermal Power Dispatch

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Abstract: *Owing to growing fuel prices, diminishing fossil assets and environmental concerns, renewable energy sources in the energy-mix are widely used. Innumerable optimization procedures perform in a different way with diverse proficiencies for solving electric power scheduling to provide continuous and maintainable electricity to specific classes of optimization problems. The paper proposes a hybrid search optimization algorithm to solve dynamic multi-objective wind-thermal power dispatch (MWTPD) by minimizing operating cost of thermal and wind units and gaseous pollutants of thermal units simultaneously and balances diversification and intensification capabilities of search. Multi-objective optimization problem is solved using non-interactive approach applying price penalty factor. The hybrid search algorithm hybridizes global search optimizer bat algorithms with local search heuristics. The bat algorithm performs global search and maintains diversity. The local search is applied to perform neighbourhood search of already visited search space for intensification with the aim to select good solution and improves convergence. The effect of valve-point-loading, power demand and generator limits are undertaken while solving dynamic MWTPD with dynamic effect. A specific search procedure is applied to get feasible solutions. The applicability of the proposed algorithms is tested on five electric power systems. The results verify that HSOA employing bat algorithm competes to recent existing algorithms.*

Keywords: **Hybrid optimization techniques, Bat algorithm, Local search, Multiobjective wind-thermal power dispatch, Ramp-rate limits, prohibited operating zone, valve-point loading effect**

Nomenclature

A. Indices

g	Iteration index
i	index of thermal unit
j	index of wind unit
k	population index
t	index of scheduling time

B. Decision variables

$P_i(t)$	real variable represents power allocated (MW) to the i^{th}committed thermal and wind units at t^{th} hour
$P_{Thi}(t)$	Real variable related to power allocated (MW) of i^{th} committed thermal unit at t^{th} hour
$P_{wj}(t)$	Real power of j^{th} committed wind generator (MW) at at t^{th} hour
$P_{ki}^{g}(t)$	real power (MW) allocated to the i^{th}committed thermal and wind units, at t^{th} hour, of k^{th} individual, during g^{th} iteration (generation)
$P_{wkj}^{g}(t)$	real power (MW) allocated to the j^{th}committed wind unit, at t^{th} hour, of k^{th} individual, during g^{th} iteration (generation)

C. Parameters

a_i, b_i, c_i, e_i, and f_i	Operating cost coefficients of i^{th} thermal unit having \$/MW^{2}h, \$/MWh, \$/h, \$/h and rad/MW, units respectively

$A_k^g(t)$	Loudness of k^{th} bat at t^{th}hour during g^{th} movement
B_{oo}, B_{io}, B_{ij}	B-coefficients of due to thermal power generator having units as MW, no units and MW^{-1}, respectively
C_{wj}	Operational electrical energy coefficient of wind generation
DR_i	Ramp-down rate of i^{th} thermal unit.
h_i	Price penalty factor of i^{th} thermal unit
P_{wRj}	Rated power of j^{th} unit by wind generator (MW)
$F_{TW}(t)$	operating cost ($/h) of thermal and wind generators at t^{th} hour
$F_{TE}(t)$	Emission of gaseous pollutants (Kg/h) of thermal generators t^{th} hour
$f_k(t)$	k^{th} bat pulse frequency during time, t
f_{min} and f_{max}	Minimum and maximum bat pulse frequency, respectively.
$F_{PW}(t)$	operating cost ($/h) of wind generators t^{th} hour
$G_{max},$	Maximum iterations for algorithm.
G_{LS1} and G_{LS2}	Maximum iterations for local search strategies.
N	total number of wind and thermal generating units
N_P	population size of bats
N_{Th}	Total number of thermal generating units.
N_W	Total number of wind generating units
N_{zi}	Number of POZ of i^{th} thermal generator
$P_{Bi}^g(t)$	Best real power of i^{th}generating units, at t^{th} hour, during gth iteration
$P_D(t)$	Power Demand t^{th} hour
P_{ij}^L	Lower bound of power for j^{th} POZ for i^{th} thermal generator
P_i^{Low}	Lower power by thermal or wind generations of i^{th} unit
P_{ij}^U	Upper bound of power for j^{th} POZ for i^{th} thermal generator
P_i^{High}	Higher power by thermal or wind generations of i^{th} unit
$P_L(t)$	Power Transmission Loss t^{th} hour
$r_k^g(t)$	Pulse emission rate of k^{th} bat at t^{th} hour during g^{th} movement
$Rand(),$	Uniform random number ∈ [0,1]
UR_i	Ramp-up rate of i^{th} thermal unit.
v_{CIj}	Cut-in Velocity (m/sec)
v_{COj}	Cut-out Velocity (m/sec)
$v_{ki}^g(t)$	velocity of k^{th} bat of i^{th} dimension at t^{th} hour, during g^{th} iteration.
v_{Rj}	Rated Velocity (m/sec)
$\alpha_i, \beta_i, \gamma_i, \delta_i, \lambda_i$	Emission coefficients of i^{th} thermal generator having Ton/MW^{2}h, Ton/MWh, Ton/h, Ton/h and MW^{-1}, units respectively
ψ, ξ, ρ, σ	Scaling constants having value > 0 and < 1.

1. INTRODUCTION

Modern daily life depends on the electrical supply generated from the generating units and distributed through networks. Owing to the escalation in power demand, there is need of increased capacities of generating stations and hence in numbers. Consequently, there is increase in the consumption of resources viz. coal, water, diesel, etc. Modern power systems around the world are increasingly complex with interconnection and power demands. Focus has shifted to improved power, improved customer focus, low cost, reliable and clean power. With this changing outlook, economic load dispatch is needed due to a lack of energy resources, increased power generation costs, and environmental concerns. In the actual scenario, the power plants are not equidistant from the load and there is no similar fuel cost function. Therefore, to provide cheaper power, loads must be distributed to various power plants to minimize power generation costs. Nowadays wind energy is competing cost with coal and gas and cheaper than majority of the renewable energy sources. Most of the countries over the world are embracing the usage of wind power the best and economical replacement of energy sources in the present energy changeover. Wind power too plays a significant role in the clean environmental by lowering greenhouse emissions of gases and thus lessening global warming. Wind power generation allows countries to diversify their energy combinations, where hydropower has great scope. The growth of wind power generation necessitates understanding its variable speed and the reduction of uncertainties associated with it. Simulation and forecasting provide information to support the decision-making process. Vargas et al. [1] conducted state-of-the-art literature review following the approach called systematic literature network analysis.

With increasing number of wind turbines, the power system operator now faces the problem of not only allocating system power among conventional generators, but also among various available wind-powered generators. The primary characteristic that differentiates wind-powered from conventional generators in the EPD problem is the stochastic nature of wind speed. It is necessary to characterize the stochastic nature of the wind speed. The classical economic dispatch model which includes wind power conversion system generator has been recently reported in [2]. A probabilistic technique has been proposed to evaluate the marginal amount of reserve capacity needed for secure operation of the power system. The objective of the proposed model is to minimize the overall operating cost based on the cost function and distribution of the electric generation of wind. Since the operating cost of the wind power is very less compared to the price of the fossil fuel-based generators, there is a possibility of over/under estimation of wind power (due to wind variability) in the EPD solution. The factors for both under and over estimation of available wind power are also included. The variability of the wind speed i.e. the future wind speed and hence the power is represented by Weibull probability distribution function. A Monte Carlo Simulation (MCS) method is used to generate a large number of scenarios to represent the volatility of wind power based on forecasting error [3]. While calculation of objective function and examination of the violation of constraints are implemented in two separated steps in proposed economic power dispatch solution. Research paper [4] deals with economic power dispatch while wind powers are modelled as inputs parameters and spinning reserve is taking into consideration. The output of wind farms changes dramatically in different periods of a day. In most scenarios, during daytime when power load is heavy, but wind output is small, while during night, the situation reverses. However, to the best of author knowledge, no study in the area consider all characteristics of the real economic dispatch problem while there are wind generation incorporated in the system simultaneously.

Soft computing is a group of procedures that target to venture the forbearance for inaccuracy and uncertainty to achieve an easy solution, sturdiness, and economical. The ingredient of soft computing methods is probabilistic reasoning, fuzzy set theory-based systems, artificial neural networks, and metaheuristic computing. The main characteristics of traditional computing are constant, rigid, precise, and illustrative. In real life, the suitability of traditional computing methods to deal with cumbersome and multifaceted problems is not promising. Conversely, the main characteristics of soft computing are random, vague, uncertain, and flexible. Liang and He [5] presented an excellent and philosophical survey on soft computing. Several metaheuristic optimization techniques are developed to get the solution of a scalar-objective economic dispatch (ED) problem. A complete survey of particle swarm optimization (PSO), its modifications and its hybrid forms to find out the global solution of the constrained economic dispatch problem is carried out [6, 7].

There is no distinct procedure to establish relation between problem features and the best-suited optimization algorithm out of the plethora of choices among metaheuristic techniques. Moreover, selection of metaheuristic techniques and its variants depends on the characteristics of a problem like multi-modality, separability, ruggedness of functional landscape etc. or the kind of correlation among a set of decision variables establishing a relation with an objective function. Each global search technique cannot be adjudged better than other optimization algorithms in all prospects, particularly when dealing with multi-dimensional and multi-modal problems [8]. Currently, optimization researchers are actively working to develop an algorithm, which can achieve a global optimal solution with high speed, better efficiency, and reliable convergence. Harman and McMinn [9] suggested that a hybrid of global and local search may be appropriate.

Inspired by the behaviour of grey wolves Pradhan et al. [10], solved EPD problems using a grey wolf optimization (GWO) [11]. The leadership behaviour in GWO is classified the wolves into alpha, beta, delta, and omega wolves. It does not have any affinity to stick in local optimum point in complex multimodal optimization problem and provide more diverse search of the solution space to solve complex EPD problem. GWO has better conveying mechanism and information sharing capabilities. It uses random function and considers three candidate's solutions for getting better results and converge quickly by performing jump from local minima towards global minima [10]. Opposition based learning (OBL) has been applied to improve the convergence rate of different optimization techniques [12]. The algorithm of GWO and swarm intelligence is hybridized by operators of mutation and crossover from evolutionary algorithms (EAs) and is called hybrid GWO (HGWO) [13]. The HGWO has been applied to solve EPD problem.

Bat algorithm (BA) [14-15] is one of these heuristic optimization algorithms, inspired by the natural behaviour of bats. The bat algorithm exploits echolocation of the bats to perform search. Mallikarjuna et al. [16] solved economic dispatch by binary bat algorithm. Adarsh et al. [17] introduced chaotic bat algorithm (CBA) for solving the economic dispatch problems with equality and inequality constraints. The bat algorithm has a good ability to explore the search area effectively, but sometimes lacks the exploitation ability while performing local search. Researchers report that its performance may diminish as the dimension increases. Such issues are true for almost all other algorithms. To remove this drawback, several methods and techniques were proposed. The hybrid bat algorithm (HBA) proposed by Fister et al. [18] has been adapted to become a hybrid self-adaptive bat algorithm (HSABA) by introduction of self-adaptation technique to the bat algorithm control parameters (loudness and pulse rate) and replaced the local search equation with differential evolution operator. Pan et al. [19] used the similar concept of parallel processing to hybridize particle swarm optimization with bat algorithm (PSO-BA).

The economic electric power generation dispatch is the allocation of power output to generators' so that the total fossil-fuel cost is minimized while satisfying the structural and operational constraints including capacity limit constraints [5]. In practice, the generator operation is restricted in certain sub-regions with the existence of prohibited operating zones (POZ). Discontinuous cost function cannot provide solution when conventional optimization methods are implemented. Owing to the increased environmental protection awareness, economic-emission dispatch (EED) becomes prevalent to minimize fossil-fuel cost and pollutants' emission, simultaneously. Literature study reveals that in recent years numerous classical methods are in use to find the solution of EED that is bi-objective and highly constrained optimization problem. Many publications have narrated the multi-objective evolutionary algorithms (MOEAs) to solve the EED problems. Qu et al. [20,21] surveyed up-to-date research associated to MOEAs like classical and dynamic EED, coordinated wind power EED and integrated EED with electric vehicles discussed Non-dominated Sorting Genetic Algorithm (NSGA), Niched Pareto genetic algorithm (NPGA) and strength Pareto evolutionary algorithm (SPEA) to solve the EED problems. Afzalan and Joorabian [22] solve EED problem using a multi-objective genetic algorithm established on the hypothesis of epsilon-dominance. Guesmi et al. [23] authenticated superior performance of NSGA-II over NSGA and NPGA. To overpower the weakness of lower diversity of the NSGA-II, a modified NSGA-II was recommended by Dhanalakshmi et al., and Muthuswamy et al, [24,25] utilizing the dynamic crowding distance and controlled elitism.

The research has been focused to achieve a global solution of a multiobjective optimization problem by applying global as well as local search procedures incorporating complex constraints. Moreover, there is no single heuristic algorithm which is capable to solve all kinds of optimization problems. Therefore, research is focussed in this area that results new algorithms every year. The hybrid search method having exclusive advantages like reliable and robust performance, global search ability, ease of implementation, little information requirement, parallelism, no need of differentiable and continuous objective function, can be a good choice to solve constrained optimization problem. The intent of this paper is to perform study of two hybrid search optimization algorithm (HSOA) to solve multiobjective wind-thermal electric power dispatch (MWTPD) problem with a balance of exploration and exploitation aspects. Large wind power conversion systems are considered. Global and local search procedures are hybridized. For global search bat algorithm is applied and for local search exploratory search and local random search are applied. To maintain a good population with diversification opposition learning strategy is applied. Bat algorithm tries to analyse and simulate the journey of bats in search of nutritious resource or chasing prey exploiting their echolocation ability. Despite, the bat algorithm has a good capability to explore the whole search area effectively, but its exploitation ability lacks behind local search techniques. The random exploratory search is hybridized with bat and grey wolf algorithms to perform a search in the neighbourhood of the optimal solution to improve the exploitation capability of search algorithms. Exploratory search improves the solution locally by perturbing the decision variables in every direction. A good population of bats is maintained by employing opposition learning strategy and diversity. The concept of algorithms is simple and is easy to implement without adjusting any parameter included in the formulation. In this multi-objective problem, the objectives of reducing operating cost of fuel and pollutant emissions are non-commensurable, imprecise and conflicting in nature. No optimal solution for the improvement of any objective is possible without sacrificing other objectives. Many approaches and methods have been proposed in recent years to solve multi-objective optimization problems. These methods are broadly grouped under two major titles: interactive and non-interactive. In the interactive method, the decision maker identifies a local preference function or trade-off among objectives and the solution process gradually proceeds towards the globally satisfactory solution. In the non-interactive method, a global preference function of the objectives is identified and optimized with respect to the constraints. The non-interactive approach is applied whereby the fuel cost and pollutants' emission is handled by the method of price penalty factors (PPF), which converts the multi-objective wind-thermal power dispatch problem into a scalar objective wind-thermal power dispatch problem. The results are validated on 13-thermal and 2-wind generators system constituting two possibilities considering transmission losses, valve-point loading effect and avoiding prohibited operating zones. Equality constraints are met using the simple search technique based on the allocation of unmet demand. Inequality constraints are fixed to their limits on the violations. The results achieved by proposed methods compared with the existing methods to show its applicability to solve wind-thermal dispatch problem.

2. WIND POWER MODEL

Wind power is clean source of renewable energy. Mostly, the wind power is used as a major constitute in electricity generation sector. Wind power generation has limitation of variability and uncertainty. Wind power is intermittent and varies from time to time. In wind power conversion system (WPCS) when wind speed is below cut-in speed $\boldsymbol{v_{CIj}}$or above cut-out speed $\boldsymbol{v_{COj}}$, no power will be generated. For a speed between cut-in and rated speed, generation is linear function of power. At wind speed between $\boldsymbol{v_{Rj}}$ and $\boldsymbol{v_{COj}}$, the output is equal to rated power generator.

$$P_{Wj} = \begin{cases} 0 & ; 0 \le v_j \le v_{CIj} \\ P_{WRj}\left(A_j + B_j v_j + C_j v_j^2\right) & ; v_{CIj} \le v_j < v_{Rj} \\ P_{WRj} & ; v_{Rj} \le v_j \le v_{COj} \\ 0 & ; v_j \ge v_{COj} \end{cases} \quad (j = 1,2,\dots,N_W) \qquad \dots(1)$$

where

$$A_j = \frac{1}{\left(v_{CIj} - v_{Rj}\right)^2}\left\{v_{CIj}\left(v_{CIj} + v_{Rj}\right) - 4v_{CIj}v_{Rj}\left(\frac{v_{CIj} + v_{Rj}}{2v_{Rj}}\right)^3\right\}$$

$$B_j = \frac{1}{\left(v_{CIj} - v_{Rj}\right)^2}\left\{4\left(v_{CIj} + v_{Rj}\right)\left(\frac{v_{CIj} + v_{Rj}}{2v_{Rj}}\right)^3 - \left(3v_{CIj} + v_{Rj}\right)\right\}$$

$$C_j = \frac{1}{\left(v_{CIj} - v_{Rj}\right)^2}\left\{2 - 4\left(\frac{v_{CIj} + v_{Rj}}{2v_{Rj}}\right)^3\right\}$$

with P_{Wj} is j^{th} WPCS output as a real power (typical units of kilowatt or megawatt), P_{WRj} is j^{th} WPCS rated power, v_{Rj}, v_{CIj} and $v_{COj}$are rated, cut-in and cut-out wind speed of j^{th} WPCS (typical units of miles/hour or miles/second), respectively, and N_w is number of WPCS. For lower wind generation P_j^{Low}, is zero and high wind generation P_j^{High} is P_{WRj}.

The cost directly proportional to output wind power is considered. The cost of wind generation, $\boldsymbol{F_{P_w}}$;

$$F_{P_W} = \sum_{i=1}^{N_w} \left[\left(C_{wj} \times P_{wj} \right) \right] \quad \text{... (2)}$$

where $\boldsymbol{C_{wj}}$ is operational electrical energy coefficient in \$/MWh.

3. MULTIOBJECTIVE WIND-THERMAL DISPATCH MODEL

The electric power dispatch (EPD) problem minimizes the overall operating cost of a power generation system $\boldsymbol{F_{TW}(t)}$ (Thermal and Wind) while meeting the load demand and transmission loss within generator limits, avoiding prohibited operating zones (POZ), satisfying ramp-rate limits, and considering valve-point loading effect on cost characteristics. The total cost function is modelled to be minimized as the sum of fuel cost of thermal units and wind cost. In power dispatch problem, emission of gaseous pollutants such as CO_2, NO_X, SO_2, are released during the operation of committed generating units while considering the operating constraints. This emission of pollutants $\boldsymbol{F_{TE}(t)}$, is minimized which is function of real power [26]:

Minimum operating cost of thermal and wind power

$$F_{TW}(t) = \sum_{i=1}^{N_{Th}} \left(a_i P_i^2(t) + b_i P_i(t) + c_i + \left| e_i sin\left\{ f_i \left(P_i(t) - P_i^{Low} \right) \right\} \right| \right) + \sum_{j=1}^{N_w} \left(C_{wj} P_{wj}(t) \right) \qquad (\$/h) \quad \text{.. (3)}$$

Minimize the emission of gaseous pollutants

$$F_{TE}(t) = \sum_{i=1}^{N_{Th}} \left(\alpha_i P_i^2(t) + \beta_i P_i(t) + \gamma_i + \delta_i e^{\lambda_i P_i(t)} \right) \quad \left(\frac{Kg}{h} \right) \quad \text{... (4)}$$

Subject to:

(i) Load demand balance equation

$$\sum_{i=1}^{N_{Th}} P_{Thi}(t) + \sum_{j=1}^{N_W} P_{Wj}(t) = P_D(t) + P_L(t) \quad \text{... (5)}$$

(ii) The active power generation limits of thermal power plant and wind generator

$$P_i^{Low} \le P_i(t) \le P_i^{High} \qquad (i = 1,2, \dots, N) \quad \text{... (6)}$$

(iii) Ramp-rate limits [9] of thermal generators

$$max\left(P_{Thi}^{Low}, P_{Thi}(t-1) - DR_i \right) \le P_{Thi}(t) \le min\left(P_{Thi}^{High}, P_{Thi}(t-1) + UR_i \right) \qquad (i = 1,2, \dots, N_{Th}) \quad \text{... (7)}$$

(iv) The prohibited operating zones (POZ) limits

$$P_{Thi}(t) = \begin{cases} P_i^{Low} \le P_i(t) \le P_{i,1}^l \\ P_{i,k-1}^u \le P_i(t) \le P_{i,k}^l \\ P_{i,N_{Zi}}^u \le P_i(t) \le P_i^{High} \end{cases} \qquad (k = 1,2,..,N_{Zi}, i = 1,2, \dots, \ N_{Th}) \quad \text{... (8)}$$

The system transmission losses are given by the relation given by

$$P_L(t) = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i(t)B_{ij}P_j(t) + \sum_{i=1}^{N} B_{io}P_i(t) + B_{oo} \quad \text{... (9)}$$

with $N = N_{Th} + N_W$ and $P_i(t) = \left[P_{Thi}(t) \mid P_{Wj}\right]^T$, a_i (\$/MW^{2}h), b_i(\$/MWh), c_i(\$/h), e_i (\$/h) and f_i (rad/MW) are thermal operating cost coefficients related to i^{th} generator. N_{Th} gives the number of committed generating units. P_i is the real power generated by i^{th} thermal generator, P_i^{max} and P_i^{min} are the maximum and minimum generation limits of i^{th} thermal generator, respectively. α_i (Ton/MW^{2}h), β_i(Ton/MWh), γ_i(Ton/h), δ_i (Ton/h) and λ_i (MW^{-1}) are thermal pollutant's emission coefficients related to i^{th} generator. P_L (MW) and P_D (MW) are transmission power loss and power demand, respectively. P_i^{Low} and P_i^{High} are the lower and upper generation limits of i^{th} thermal generator, respectively. UR_i and DR_i are up and down ramp-rate limits, respectively, of i^{th} thermal generator, $P_{i,j}^{U}$ and $P_{i,j}^{L}$ are higher and lower bounds of j^{th} POZ for i^{th} thermal generator, respectively. N_{zi} gives the number of POZ of i^{th} thermal generator. $P_i(t-1)$ is the power of previous generation for i^{th} thermal generator, $B_{OO}\ (MW), B_{iO}\ and\ B_{ij}(MW^{-1})$ are B-coefficients.

In this multi-objective problem, the objectives of reducing operating cost of fuel and pollutants' emissions simultaneously are non-commensurable, imprecise and conflicting in nature. No optimal solution for the improvement of any objective is possible without sacrificing other objectives. To solve multi-objective optimization problems, there are two major approaches: interactive and non-interactive. In the interactive method, the decision maker identifies a local preference function or trade-off among objectives and the solution process gradually proceeds towards the globally satisfactory solution. The decision maker is the key player in the multiple criteria decision-making process and is responsible for the selection of the best solution among all the generated solutions. In the non-interactive method, a global preference function of the objectives is identified and optimized with respect to the constraints. The non-interactive nature of fuel cost and pollutants' emission is handled by the method of price penalty factors (PPF), which converts the multi-objective wind-thermal power dispatch problem into a scalar objective wind-thermal power dispatch problem. The price penalty factor (PPF) is defined as the ratio of the total fuel cost at maximum power to total emissions at maximum power of the particular generator.

The multi-objective optimization problem can be solved by converting it into scalar objective constrained optimization problem.

$$\text{Minimize} \quad F(t) = F_{TW}(t) + h\, F_{TE}(t) \quad \text{... (10)}$$

Subject to constraints given by Eqs. (5), (7), (8) and (9)

$$\text{where } h = \frac{\sum_{i=1}^{N_{Th}}\left(a_i\left(\mathrm{P}_i^{High}\right)^2 + b_i\mathrm{P}_i^{High} + c_i + \left|e_i \sin\left\{f_i\left(\mathrm{P}_i^{High} - P_i^{Low}\right)\right\}\right|\right)}{\sum_{i=1}^{N_{Th}}\left(\alpha_i\left(\mathrm{P}_i^{High}\right)^2 + \beta_i\mathrm{P}_i^{High} + \gamma_i + \delta_i e^{\lambda_i \mathrm{High}}\right)} \quad (\$/Kg)$$

A dynamic-programming algorithm runs backward in time starting from the final hour, back to the initial hour. Conversely, the algorithm can run forward in time from the initial hour to the final hour. The forward approach has distinct advantages in solving generator dynamic scheduling problem. In order to have separability of the objective function, the objective function shown in Eq. (10) is rewritten as

$$F = \sum_{t=1}^{T} F(P(t)) \quad (\$) \quad \text{... (11)}$$

Applying forward approach, the minimization process is given as.

$$F(P(t)) = minimize \left(F(P(t)) + \sum_{\tau=1}^{t-1} F^*(P^*(\tau))\right) \quad (\$/h) \qquad (t = 1,2,,,T) \quad \text{... (12)}$$

Subject to all the constraints shown in Eqs. (5) to (8).
where $P^*(t)$is the optimal values of t^{th} interval giving minimum cost $F^*(P^*(t))$.

The proposed hybrid search optimization algorithms are employed to search the power generation; $P_i(t)$ $(i = 1,2,\dots,N)$ to minimize operating cost given by Eq. (10) while the constraints given by Eqs. (5) to (8) are satisfied.

3.1 Constraint handling

Electric power thermal generation handles the constraints as given below:

3.1.1 Generation limits of thermal units

Each generator has the power generation limits that it can generate. On violation of either limit, the generation is fixed to its respective limit.

$$P_i(t) = \begin{cases} P_i^{min} & ; P_i(t) < P_i^{min} \\ P_i^{max} & ; P_i(t) > P_i^{max} \\ P_i(t) & ; P_i^{min} \le P_i(t) \le P_i^{max} \end{cases} \quad (i \in [1, N]) \qquad \dots(13)$$

where

$$P_i^{min} = \begin{cases} max\left(\mathrm{P}_{Thi}(t-1) - DR_{Thi}, P_{Thi}^{Low}\right) & ;\text{Ramp rate limits} \\ P_{Thi}^{Low} & ;\text{without ramp-rate limits} \end{cases} \quad (i \in [1, N_{Th}]) \qquad \dots(14a)$$

$$P_i^{max} = \begin{cases} min\left(\mathrm{P}_{Thi}(t-1) + DR_i, P_{Thi}^{High}\right) & ;\text{Ramp rate limits} \\ P_{Thi}^{High} & ;\text{without ramp-rate limits} \end{cases} \quad (i \in [1, N_{Th}]) \qquad \dots(14b)$$

3.3.2 Prohibited operating zone (POZ)

To avoid the POZ, the inequality constraints are taken care by perturbing the generation of i^{th} generator randomly of k^{th} bat during t^{th} movement using the following expression. The generation falling in the prohibited zone is fixed to its either lower or upper value of POZ based upon the generation lies near to the lower or upper limit, respectively.

$$P_i(t) = \begin{cases} P_{ij}^L - R(0,1)\left(1 - \dfrac{P_{ij}^L}{P_{i,j-1}^U}\right) & ;\ If\left(P_i(t) - P_{ij}^L\right) \le \left(P_{i,j-1}^U - P_i(t)\right) \\ P_{i,j-1}^U + R(0,1)\left(1 - \dfrac{P_{ij}^L}{P_{i,j-1}^U}\right) & ;\ otherwise \end{cases} \quad (i \in [1, N_{Th}]) \qquad \dots(15)$$

3.3.3 Equality Constraint

The equality constraint to meet the demand for k^{th} bat during g^{th} generation (iteration), given by Eq. (12) is taken care by perturbing the generation randomly in such a manner so that Eq. (12) is satisfied. The perturbation, in reference to the difference in the demand constraint, is distributed among the generators selecting randomly. The difference in power demand constraint given by Eq. (12) of k^{th} member is computed as

$$\Delta P_D(t) = P_D(t) + P_L(t) - \sum_{i=1}^{N} P_i(t) \qquad \dots(16)$$

The generators share unmet power demand given by Eq. (16). Sharing is done among generators by selecting them randomly to satisfy equality constraint given by Eq. (16).

Randomly selected m^{th} generating unit, $P_m(t)$ of is updated as given by the equation:

$$P_m(t) = \begin{cases} P_m(t) - min\left(\Delta P_m^{min}, |\Delta P_D(t)|\right) & ;\ \Delta P_D(t) < 0 \\ P_m(t) + min\left(\lceil \Delta P_D(t) \rceil, \Delta P_m^{max}\right) & ;\ \Delta P_D(t) > 0 \end{cases} \qquad \dots(17)$$

where $\Delta P_m^{min} = R(0,1)\left[P_m(t) - P_m^{min}\right](|\Delta P_D(t)|/P_D)$,

$\Delta P_m^{max} = R(0,1)[P_m^{max} - P_m(t)](|\Delta P_D(t)|/P_D)$,

This generation updating is repeated till $|\Delta P_D(t)| \le \varepsilon$ is achieved.

4. HYBRID SEARCH OPTIMIZATION ALGORITHM

The hybrid search optimization algorithm for wind-thermal economic power dispatch considers bat algorithm as global search techniques. The exploratory and local search procedures are hybridized for local search. Opposition-learning strategy maintains good-solutions and diversity. Each algorithm requires the initialization of bats and their fitness is evaluated for feasible solutions. The constrained handling procedure follow the updating or adjustment of variables. The follow sections consider the hybrid search optimization procedures.

4.1 Random Initialization

There are N_P number of flying bats specified by a vector. The location of all flying bats or grey wolves is represented by the matrix given as:

$$P^g(t) = \begin{bmatrix} P_{1,1}^g(t) & P_{1,2}^g(t) & \dots & P_{1,N}^g(t) \\ P_{2,1}^g(t) & P_{2,2}^g(t) & \dots & P_{2,N}^g(t) \\ \dots & \dots & P_{k,i}^g(t) & \dots \\ P_{N_P,1}^g(t) & P_{N_P,2}^g(t) & \dots & P_{N_P,N}^g(t) \end{bmatrix}_{N_P \times N} \quad and\ P_K^g(t) = \left[P_{k1}^g(t), P_{k2}^g(t), \dots P_{kN}^g(t)\ \right]^T$$

where the $P_{ki}^g(t)$ represents the i^{th} dimension of k^{th} flying bats. The search space is $[N_P \times N]$. $P_k^g(t)$ is a vector of N-dimension and representing k^{th} bat for g^{th} movement (iterations).

A uniform distribution is used to allocate the initial (t = 0) location of each flying bats

$$P_{ki}^g(\mathrm{t}) = P_i^{lower} - R(0,1)\left(P_i^{upper} - P_i^{lower}\right) \quad \left((i \in [1, N_{Th}], k \in [1, N_P]\right) \qquad \dots(18)$$

4.2 Fitness evaluation

The fitness of location of each flying bat is calculated by putting the values of decision variable into a user defined fitness function and the corresponding values are stored in the following array:

$$F^g(t) = \left[F_1^g\left(P_1^g(t)\right) \quad F_2^g\left(P_2^g(t)\right) \quad \dots \quad F_{N_P}^g\left(P_{N_P}^g(t)\right)\right]_{N_P \times 1}^T$$

The fitness value of each flying bat is computed using Eq. (10) whereby equality and inequality constraints are satisfied by applying the procedure explained below. The location depicts the quality of food source searched by it and hence their probability of survival.

4.3. Bat Algorithm

Xin-She Yang [14] developed Bat algorithm in 2010 based on echolocation of the bats. A bat uses sonar and echo techniques to detect the obstacles and their avoidance. Generally, sound pulses reflected from the obstacles are converted into a frequency. From emission to reflection, bats navigate with the time delay. Bats (normal pulse rate is 10 to 20 times per second) emit the short and loud sound impulses. The hitting and reflecting helps to guess the position of prey. The bats convert their own pulse into useful information to judge the position of the prey. The useful wavelengths for the bats, from 0.7 to 17 mm. The inbound frequencies are in the range of $20 - 500$ kHz. The algorithm selects the pulse frequency and the rate, initially. The pulse rate is taken between the range from 0 to 1. Zero means that there is no emission of pulses and one means that the bat's emitting pulses at their maximum rate. Basically, the bats sense the distance using echolocation. The bats judge the difference between the food/prey and background barriers [15].

4.3.1 The echolocation

A bat emits pulses, from the echoes (feedback), the bat can know if the food exists around these two bats or not. The best position is determined by the objective fitness, around the randomly selected bat. A better fitness value confirms the existence of food. If the food is confirmed to exist around the two bats, the current bat moves to a direction at the surrounding neighbourhood of the two bats where the food is supposed to be plenty otherwise, it moves toward the best bat. The bats' movements are given by:

$$v_{ki}^{g+1}(t) = v_{ki}^{g}(t) + \left(P_{ki}^{g}(t) - P_{i}^{B}(t)\right) f_k(t) \quad (i \in [1, N], k \in [1, N_P]) \qquad ...(19)$$

The $m \in [1, N_P]$, is location of randomly selected bat. P_i^B is the best solution. The frequency, f of the bat pulse is updated as follows:

$$f_k(t) = f_{min} + (f_{max} - f_{min})R(0,1) \qquad (k \in [1, N_P]) \qquad ...(20)$$

The position of the bat is updated within the prescribed limits using the equation:

$$P_{ki}^{g+1}(t) = \begin{cases} P_{ki}^{g}(t) - min\left\{v_{ki}^{g+1}(t), \left|\left(P_{ki}^{g}(t) - P_{i}^{min}\right)\right|\right\}; v_{ki}^{g+1}(t) < 0 \\ P_{ki}^{g}(t) + min\left\{v_{ki}^{g+1}(t), \left|\left(P_{i}^{max} - P_{ki}^{g}(t)\right)\right|\right\}; v_{ki}^{g+1}(t) > 0 \end{cases} (i \in [1, N], k \in [1, N_P]) \quad (21)$$

The direction of movement generated by Eq. (21) directed towards the bat with the best position. This mechanism allows the bat algorithm to exploit more around the best position. There is a risk that the solutions generated by such moves could be trapped in local optima if the moves are not far enough and can lead to a premature convergence. At the initial stages of iterations, the proposed movement (Eq. 21) could enhance the exploration capability, and at the end of the iteration process it has stronger exploitation ability.

4.3.2 Random walk

The *rand* is a uniform random number generated within 0 and 1. Based on the pulse rate change, the bat position is locally updated and remembered as

$$P_{ki}^{g+1}(t) = P_{Bi}^{g}(t)[2\, R(0,1) - 1]A_v(t) \quad (i \in [1, N], k \in [1, N_P]) \qquad ...(22)$$

$$where\ A_v(t) = \frac{1}{N_P}\sum_{i=1}^{N_P} A_i(t)$$

The position of the bat, P_{ki}^{g+1} is adjusted within the limits of search space during next iteration as stated:

$$P_{ki}^{g+1}(t) = \begin{cases} P_i^{min} + R(0,1)\left(P_{ki}^{g}(t) + P_i^{min}\right) & ; P_{ki}^{g+1}(t) < P_i^{min} \\ P_i^{max} - R(0,1)\left(P_i^{max} - P_{ki}^{g}(t)\right) & ; P_{ki}^{g+1}(t) > P_i^{max} \\ P_{ki}^{g+1} & ; P_i^{min} \le P_{ki}^{g+1}(t) \le P_i^{max} \end{cases} \quad (i \in [1, N], k \in [1, N_P]) \ ...(23)$$

Fitness based tournament selection, where the competitors are the old and new solutions, is implemented.

$$P_{ki}^{g+1}(t) = X_{ki}^{g}(t)\,, \qquad if F\left(X_{ki}^{g}\right) < F\left(P_{ki}^{g+1}\right) and\ A_k^g(t)\ \forall\ (k \in [1, N_P]) \qquad ...(24)$$

The fit solution replaces the less fit one, with a probability$A_k^g(t)$.

4.3.3 Loudness and pulse emission rate

In order to provide an effective mechanism to control the exploration and exploitation. When switching from exploration to exploitation stage is necessary, the loudness, A_i and the pulse emission-rate, 'e_i' are varied during the iterations. Since, the loudness usually decreases once a bat has found its prey, while the rate of pulse emission increases. The loudness can be chosen between A_{min} and A_{max} assuming, $A_{min} = 0$ means that a bat has found the prey and temporarily stop emitting any sound.

$$A_k^{g+1}(t) = (\psi\, R(0,1) + \xi)A_k^g(t) \ \ (k \in [1, N_P]) \qquad ...(25)$$

$$r_k^{g+1}(t) = \{1 - exp(-\rho\, R(0,1))\}r_k^g(t) \quad (k \in [1, N_P]) \qquad ...(26)$$

The new position of k^{th} bat is determined from the previous position of $(k - 1)^{th}$ bat. Where ψ, ξ and ρ are constants. 'ψ' and 'ξ' has less than 1 value such that their sum is 1. Preferably, 'ψ' is taken as the golden number $\left(\sqrt{5}-1\right)/2$. $rand()$ are uniform random variables between 0 to1.

4.4 Local Search Strategies

In the local search, the current solution point is explored in negative as well as positive directions along each variable. The solution having a best objective function is carried forward. Presume, that the current solution is denoted by $\boldsymbol{P_{ki}^{g}(t)(i = 1, 2, \ldots, N)}$ by and its corresponding objective function is $\boldsymbol{F_{k}^{g}}$. The current solution is perturbed by a small possible change till minimum objective function value is achieved. The perturbation is computed as described as:

$$\boldsymbol{P_{ki}^{P} = \begin{cases} P_{ki}^{g}(t) + min\left(\delta P_j(t), \left|P_j^{max} - P_{kj}^{g}\right|\right) & ; i = j \\ P_{ki}^{g}(t) & ; i \neq j \end{cases} (j \in [1, N]; k \in [1, N_P])} \quad \ldots(\mathbf{27})$$

$$\boldsymbol{P_{ki}^{N} = \begin{cases} P_{ki}^{g}(t) - min\left(\delta P_j(t), \left|P_j^{max} - P_{kj}^{g}\right|\right) & ; i = j \\ P_{ki}^{g}(t) & ; i \neq j \end{cases} (j \in [1, N]; k \in [1, N_P])} \quad \ldots(\mathbf{28})$$

$$\boldsymbol{where\ \ \delta P_j(t) = P_D(t) \frac{\left(P_i^{max} - P_i^{min}\right)}{\sum_{i=1}^{N}\left(P_i^{max} - P_i^{min}\right)} \mu\left(1 - \frac{g}{G_{max}}\right)}$$

with G_{max} is the maximum number of iterations.

Find the best value objective and save corresponding power generations.

$$F_{ki}(t) = \min\{F_{ki}^{P}(P_{ki}^{P}(t)), F_{k}^{N}(P_{ki}^{N}(t)), F_{ki}(P_{ki}^{g}(t))\} \qquad (i \in [1, N]) \quad \ldots(29)$$

$$F_k(t) = \min\{F_{ki}(t)(i = 1,2, \ldots, N)\} \qquad (k \in [1, N_P]) \quad \ldots(30)$$

In case, $F_k(t)$ is better than $F_k^g(t)$ then is preserved and again the power generation is perturbed. In case, $F_k(t)$ is not better than $F_k^g(t)$ then $\delta P_i(t)$ is reduced by a multiplying parameter, λ and the power generation is perturbed to seek better objective function. Multiplying parameter is computed by using Chaotic sequence and is defined below:

$$\mu = 4\mu(1 - \mu) \quad ; \mu \notin \{0, 0.25, 0,5, 0.75, 1\} \quad \ldots(31)$$

The computation time can be refined by initiating with a better solution (near to optimal) by inspecting the opposite solution simultaneously. This approach has been implemented to initial solutions as well as implemented during iterative process.

$$P_{li}^{g}(t) = P_i^{L}(t) + P_i^{U}(t) - P_{ki}^{g}(t) \qquad (i \in [1, N];\ l = k + N_P;\ k \in [1, N_P]) \quad \ldots(32)$$

where $P_i^U(t) = max\{P_{ki}^g(t)\ ; (k = 1,2, \ldots N_P)\}$ and $P_i^L(t) = min\{P_{ki}^g(t)\ ; (k = 1,2, \ldots N_P)\}$

The opposite current point, $P_{li}^g(t)$ is updated to move towards the best solution, $P_{Bi}(t)$.

$$P_{li}^{g}(t) = P_{Bi}^{g}(t) + \sigma\left(P_{Bi}^{g}(t) - P_{li}^{g}(t)\right) \quad (i \in [1, N];\ l = k + N_P\ ; k \in [1, N_P]) \quad \ldots(33)$$

where σ is a factor lies between 0.618 to 1 and uyy7pdated iteratively based on the random number. In case Eq. (41) is applied single handed then out of $2N_P$ solutions, best N_P solutions are retained for further movement. Stepwise procedure for hybrid search optimization algorithm(s) is given below as Algorithm-I

Algorithm-I: Proposed HSOA

Objective function $F_k(P), P_k(t) = [P_{k1}(t), P_{k2}(t), \ldots P_{kN}(t)]^T$
Input parameters
Set time interval, $t = 0$
$\boldsymbol{WHILE}\ (t < T)$
  Increment the time-interval, $t = t + 1$
  Initialize the population $P_{ki}^{o}(t)$ using *Eq.* (17)
  Compute feasible solution using *Eqs.*(18-21) and compute fitness function $F_k^o(t)$ using *Eq.* (10).
  Find the best solution $F_k^o(t)$ and $F_{Bi}^o(t)$ $(i \in [1, N])$ and term as global $G_B(t)$ and $P_{Gi}(t)(i \in [1, N])$
  $g = 0$
  $\boldsymbol{WHILE}\ (g < G_{max})$
    $g = g + 1$
    Apply the global search bat algorithm
    Echolocation, Random Walk and Update Loudness and emission rate
    Arrange the population rank-wise based on their fitness function and find the current best solution, $F_B(t)$, and $P_{Bi}(t)$
    $\boldsymbol{FOR}\ g_1 = 1, G_{RES}$
      $\boldsymbol{FOR}\ k = 1, N_P/m$
        Update current positions of individuals in the neighbourhood by Eqs.(27,28)
      $\boldsymbol{ENDFOR}$
      Apply opposition-based learning using Eq.(32)
      $\boldsymbol{IF}\left(F_B^g(t) < G_B(t)\right)\boldsymbol{THEN}$
        Update $G_B(t)$ and its corresponding generation, $P_{Gi}(i \in [1, N])$
        $\boldsymbol{ELSE}$
          $\boldsymbol{FOR}\ g_2 = 1, G_{LS}$
            Apply neighbourhood search to update current positions using Eqs. (32-33)
          $\boldsymbol{ENDFOR}$
      $\boldsymbol{ENDIF}$
    $\boldsymbol{ENDFOR}$
  $\boldsymbol{ENDDO}$
  Save the global solution for t^{th} interval
$\boldsymbol{ENDDO}$
$\boldsymbol{STOP}$

5. TEST SYSTEMS

The validity of the hybrid search optimization algorithm (HSOA) for wind thermal scheduling problem has been demonstrated on Two test systems detailed in Table-I. A system consists of 15-generator system out of which thirteen generators are thermal and two generators are wind. Thermal generators follow ramp-rate and prohibited operating zone [8,26,27] constraints. The wind generator parameters are shown in Table-II. The hourly wind velocity for 12 hours [27] is given in Table-III. Pollutant's emission characteristics are taken from [26]. The input parameters viz number of generators, N, the number of bats, N_P, maximum number of local search iterations, G_{RES}, minimum frequency, $f_{\min}$ and maximum frequency, $f_{\max}$ etc. undertaken to implement HSOA algorithm is given in Table-IV. These parameters are set after performing simulations. Minimum frequency, f_{max} and maximum frequency, f_{min} for bat are set to 0 and 2, respectively for all the test systems. Opposition factor, F_{opp}, and local random search iterations, G_{LS} are set to 0.6 and 20, respectively for both the algorithms and for all the test systems. The maximum number of function evaluations (NFE) are evaluated during each iteration. $'\psi'$ is taken equivalent to the golden number 0.618. $'\xi'$ is taken as 0.382 and $'\rho'$ is set 76.4. To verify the achievement of a global solution, thirty independent trail runs are performed

Table-I. Test System Details

Test System	Category of test System	No. of Generators, N Thermal + Wind $N_{Th} + N_W$	Power Demand P_D (MW)	Time Horizon T (h)	Ramp-Rate (RR)	Prohibited Operating Zones (POZ)	Transmission Loss P_L	[Ref]
TS1	Small	13+2	2630	1	√	√	√	[18,26]
TS2	Small	13+2	2630	12	√	√	√	[26,27]

Table-II. Wind generator parameters [8]

Parameters	Wind Generator 1	Wind Generator 2
Cut-in Speed, v_{CIi} (m/s)	4	4
Rated Speed, v_{ri} (m/s)	14	14
Cut-out Speed, v_{COi} (m/s)	25	25
Direct electrical energy cost coefficient, C_{wj} ($/MWh)	120	120

Table-III. Wind speed for 12 hours [27].

Time (h)		1	2	3	4	5	6	7	8	9	10	11	12
Wind speed (m/s)	V_1	5.788	5.358	5.829	7.193	7.989	7.559	7.250	7.063	7.591	6.165	6.414	7.035
	V_2	8.284	8.149	9.446	9.134	8.284	7.190	6.826	9.836	8.127	8.213	8.966	10.202

Table-IV. Input parameters for HSOA algorithms

Parameters	TS1	TS2
Number of bats, N_P	50	100
Maximum number of iterations, G_{Max}	30	35
Maximum exploratory search iterations, G_{LS}	40	10

6. SIMULATION OF RESULTS

The algorithms are run thirty times to record the minimum, mean, maximum and standard deviation of total electric power generation cost for all the test systems so that global solution is ascertained for each case.

Test system, TS1: Hybrid search optimization algorithm is implemented for one interval with the aforementioned parameters and achieved results are depicted in Table-V when wind velocity for the generator is 8 m/s and 16 m/s. Table-V also presents the results of power dispatch when all thermal generators are considered. The emission of pollutants is also presented at the achieved schedule. This test system considers 14 and 15 as wind generators and rest of generators are thermal generators. The effect of wind velocity variation on wind generator cost is observed and results are depicted in Table-VI where $|\Delta P_D|$ achieved is better that 0.1×10^{-4}. It is observed that as the wind cost increases, there is decrease in thermal operating cost giving rise to overall operating cost. The algorithm gives competing results with small SD (< 1) except for wind speed 8 m/h and 10 m/s. The variation of iteration versus number of evaluations of NFEs is shown in Fig.1 for 16 m/s wind velocity. The minimum operating cost is achieved in 12 iterations as shown in Fig.2 for 16 m/s wind velocity.

Table-VII gives the effect of emission of pollutants with the inclusion of wind energy conversion systems. It is observed that emission of pollutants is decreased (negative sign) but the overall operating cost increases if the wind velocity is more than 6 m/s for TS1.

Table-V. Results of test system TS1.

Parameters	Wind and thermal dispatch		All thermal dispatch [28]
V_1 (m/s)	8	16	-
V_2(m/s)	8	16	-
P_1(MW)	390.8641	352.2218	454.9995
P_2(MW)	203.4497	185.6653	379.9996
P_3(MW)	129.9771	130	130
P_4(MW)	130	130	130
P_5(MW)	170	169.9974	170
P_6(MW)	459.9978	459.9915	460
P_7(MW)	409.6001	370.3327	430
P_8(MW)	160	160	70.1478
P_9(MW)	162	162	60.2593
P_{10}(MW)	159.9997	160	159.9599
P_{11}(MW)	79.99999	80	79.9996
P_{12}(MW)	79.99828	79.99925	79.9999
P_{13}(MW)	85	85	25.0007
P_{14} (MW)	26.01337	75.2	15
P_{15}(MW)	26.01337	75.2	15.0009
$\sum_{i=1}^{N} P_i$	2672.914	2675.6080	2660.367
P_L(MW)	42.9136	45.6079	30.8203
P_D(MW)	2630.0	2630.0	2630.0
F_{PW}^{Min}($/h)	31970.180	30992.80	30701.21
F_{Th}^{Min}($/h)	264.45190	19991.06	-
F^{Min}($/h)	49517.97	66030.91	-
E_{Th}(Ton/h)	49525.93	66031.10	32701.22
F^{Mean}($/h)	49540.13	66032.09	32701.22
F^{Max}($/h)	7635.8890	6647.8790	11101.66
SD ($/h)	5.876170	0.230051	0.005
NFE (Avg.)	92890	92724	-
NFE	92692	92442	-

Table-VI. Variation of wind speed for TS1 system when N_P=30 and P_D=2630 MW

Wind Speed, v_i (m/h)	Operating Cost, ($/h)						Average NFE	P_L (MW)
	Minimum Cost			Overall Mean Cost, F^{Mean}	Overall Maximum Cost, F^{Max}	Standard Deviation (SD)		
	Wind F_{PW}^{Min}	Thermal F_{Th}^{Min}	Overall F^{Min}					
4	32265.77	121.4768	50395.18	50395.89	50397.91	0.667716	460303	43.6743
6	32173.69	165.6461	50118.72	50119.61	50121.66	0.749412	460280	43.3606
8	31969.98	264.4519	49516.88	49518.96	49525.50	1.939245	460251	42.9219
10	31661.02	417.8942	48626.94	48630.27	48634.75	1.896214	460228	42.8174
12	31254.41	625.9729	47502.69	47504.21	47505.64	0.724516	450098	44.0549
14	30992.80	764.4832	46804.25	46804.34	46804.39	0.038762	460033	45.6086

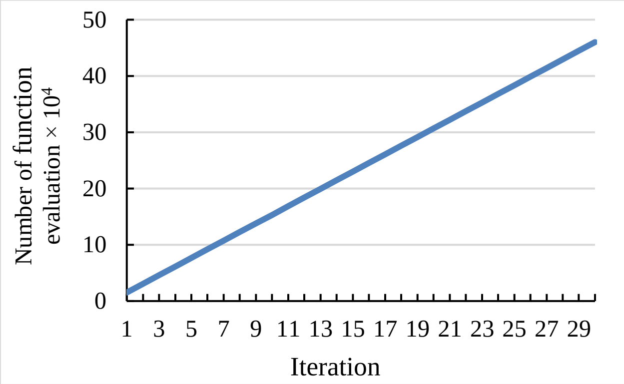

Fig. 1. Variation of number of function evaluation versus Iterations (TS)

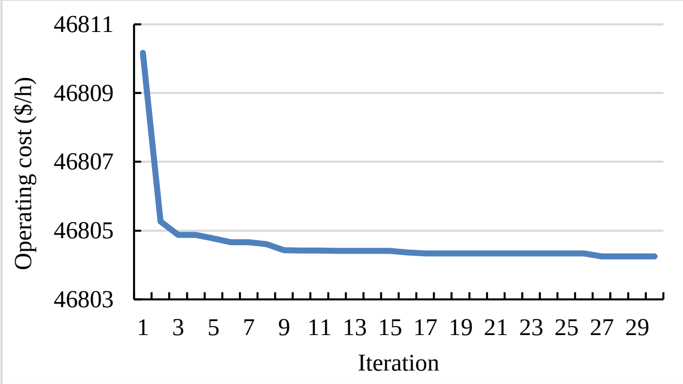

Fig. 2. Variation of operating cost versus iterations (TS)

Table-VII. Effect on overall cost and emission of pollutant's when wind power systems are included

Wind velocity, v_i (m/s)	TS1: 13 Thermal and 2 wind power Generator			
	Overall Cost, F ($/h)	Pollutant's emission E_{Th} (Ton/h)	Change in overall cost, ΔF ($/h)	Change in emission ΔE (Ton/h)
4 m/s	50395.18	121.4768	7956.02500	-1116.49
6 m/s	50118.72	165.6461	7855.04600	-1208.61
8 m/s	49516.88	264.4519	7635.49600	-1412.28
10 m/s	48626.94	417.8942	7311.02200	-1721.44
12 m/s	47502.69	625.9729	6902.03800	-2127.85
14 m/s	46804.25	764.4832	6647.84700	-2389.46

ΔF= (Cost of wind and Thermal) – (Cost for all thermals)
ΔE= (Pollutant's emission of wind and Thermal) – (Pollutant's emission for all thermals)

Test system, TS2: Hybrid search optimization algorithm (HSOA) is implemented for 12 hours with one-hour interval with the aforementioned parameters and achieved results are depicted in Table-VIII when wind velocity for both the generators is given Table-III. The ramp-rates are evaluated with reference to the power of previous time-interval. Table-VIII shows that HSOA achieved results in number of NFE. The achieved generation schedule for the TS2 for 12h time-horizon by implementing HSOA is given in Table-X.

7. STATISTICAL ANALYSIS

Box plot analysis for hybrid search optimization technique is drawn for the total generation cost as shown in Fig. 3 and Fig. 4 for TS1 for wind velocity 8 m/s and 16m/s for 1 hour, Fig. 5 for TS2 for 12 hr, Box plot shows the small variation in the quartiles giving the supremacy of results achieved. All the quartile proportions are not uniform.

Table-VIII. Comparison of TS2 using HSOA

Description	Operating cost ($/hr)			Standard Deviation (SD)
	Minimum	Mean	Maximum	
Wind Cost ($)	3195.8670	3195.8670	3195.8670	0.00
Thermal Cost ($)	386154.10	386153.10	386162.20	3.196047
Overall Cost ($)	583407.80	583408.00	583408.20	0.099478
Pollution (Ton)	85736.04	-----	85732.61	-----
NFE	6026578	6027265	6028009	$3.5612\times10^{+02}$

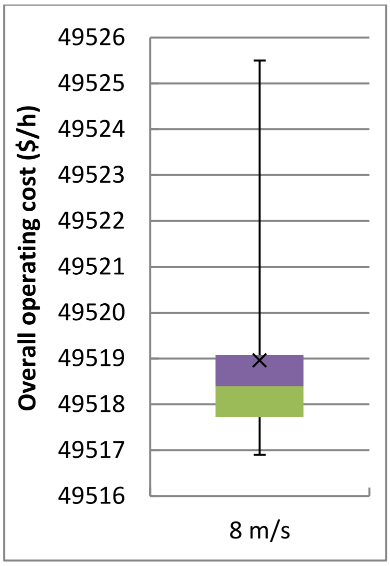

Fig 3 Box plot for TS1 (1 hr)

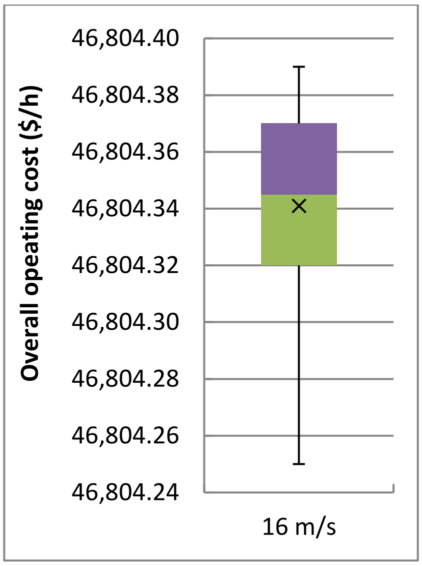

Fig 4 Box plot for TS1 (1 hr)

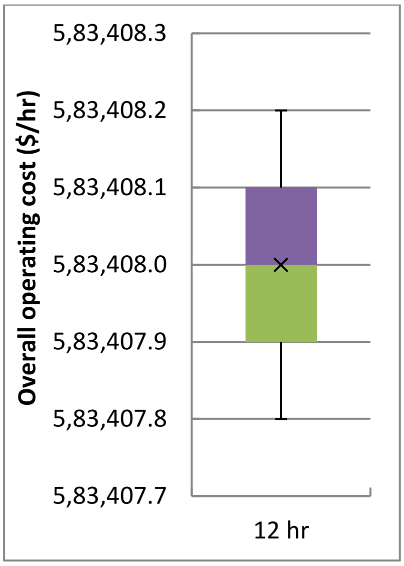

Fig 5 Box plot for TS2 (12 hr)

Table -IX. Z and p-Values obtained by performing Wilcoxon sign rank test.

Test system		HSOA			
		Z-values	p-values	R+	R−
TS1	Case-I	2.864568	0.002088	160	306
	Case-II	1.044166	0.148784	0	203
TS2		7.418520	5.9×10^{-14}	465	0

Case-I: All wind generators are having 8 m/s wind velocity
Case-II: All wind generators are having 16 m/s wind velocity

To check the validity of HSOA algorithms, a non-parametric Wilcoxon sign-rank test has been performed for all the five test systems independently with a 5% significance level. The *p*-values obtained are given in Table-IX. The p- values less than 0.05 indicates that there is a significant difference between the proposed HSOA otherwise there is no significant difference between the compared algorithms. In this *p*-values are less than 0.05 in all the test systems. It advocates that the proposed algorithm is superior. HSOA has better R (+) values for TS1, case-I and TS2

Table-X. Generation schedule of TS2 using HSOA algorithm

Time k	1	2	3	4	5	6	7	8	9	10	11	12
P_{k1} (MW)	383.7448	339.8957	327.0091	326.2095	325.4224	328.5154	329.9266	323.8996	327.0853	328.8254	327.17	323.9907
P_{k2} (MW)	225.0015	181.1018	173.8322	173.4075	173.8319	175.2169	175.4816	173.1481	174.2265	175.196	173.8712	172.4193
P_{k3} (MW)	130	130	130	130	129.9999	130	130	130	130	130	130	130
P_{k4} (MW)	130	130	130	129.9999	130	129.9983	130	130	130	130	130	130
P_{k5} (MW)	170	250	260.3898	260.2292	260.952	262.8015	262.7129	259.2296	260.7665	262.164	260.2404	258.1064
P_{k6} (MW)	460	460	460	460	460	460	460	460	460	460	459.9997	460
P_{k7} (MW)	403.7481	356.1249	341.0342	340.6173	341.4788	343.6229	344.6631	339.0421	342.4789	343.91	342.883	338.123
P_{k8} (MW)	160	225	240.8076	239.0642	239.5811	240.4414	241.4802	239.0741	240.2037	241.0153	240.4803	238.5711
P_{k9} (MW)	162	162	162	162	162	162	162	162	162	162	161.9998	162
P_{k10}(MW)	160	160	160	160	160	160	159.9998	160	160	160	160	160
P_{k11}(MW)	80	80	80	80	80	80	80	80	80	80	80	80
P_{k12}(MW)	80	80	79.99949	80	79.99963	80	80	80	80	80	80	80
P_{k13}(MW)	85	85	85	85	85	85	85	85	85	85	85	84.99995
P_{k14}(MW)	15.57893	14.31375	15.71254	21.44488	25.94522	23.4084	21.73884	20.79077	23.58863	16.89256	17.86491	20.65286
P_{k15}(MW)	27.82928	26.95257	36.38792	33.91174	27.82928	21.42953	19.65671	39.66708	26.81202	27.36514	32.63258	42.93032
$\sum P_{ki}$	2672.903	2680.389	2682.173	2681.884	2682.04	2682.434	2682.66	2681.851	2682.162	2682.368	2682.142	2681.794
P_{kL}(MW)	42.90259	50.38867	52.17286	51.88430	52.04029	52.43431	52.65991	51.85133	52.16161	52.36839	52.14185	51.79370
F_{kW} ($/h)	234.2418	223.7858	287.7763	295.2159	275.4270	225.7146	208.1024	328.2600	259.7644	236.5865	273.0709	347.9213
F_{kTh} ($/h)	32059.32	32251.38	32180.98	32142.71	32161.09	32257.89	32296.48	32090.06	32197.44	32263.59	32196.33	32056.77
F_k($/h)	49817.58	48782.98	48479.62	48385.59	48416.00	48646.34	48737.05	48263.79	48504.45	48671.12	48513.41	48189.89
E_{kTh}(Ton/h)	7742.229	7204.898	7073.700	7045.778	7059.840	7140.799	7171.610	7000.631	7089.778	7144.426	7088.348	6974.003
NFE	502255	502260	502346	502251	502432	502141	502388	502435	502219	502343	502103	502263

8 CONCLUSION

With the inclusion of renewable sources of energy in the problem, the dispatching of load demand with wind and thermal units, was simulated and it was concluded that the fuel cost of the thermal generating units and transmission losses (due to power transfer from thermal units to load centre) both reduce. This was due to the sharing of load by the renewable sources, the power generation by thermal units reduces and finally fuel cost reduces keeping the energy balance and other constraints within limits. This work has employed the nature inspired bat algorithm on the constrained multiobjective wind-thermal power dispatch problem. Price penalty factor is ued to convert multiobjective optimization problem into scalar objective optimization problem since operating cost and gaseous pollutions are function of generation of thermal plants only. It has providing the optimal solution satisfying the operating capacity, power balance constraints for the MWTPD problem with Fifteen generator (thirteen conventional generators and two wind power generator). The dynamic MWTPD problem is also solved and attained results are satisfactory. The algorithm executed for thirty independent trial runs with the test system and the solutions are analysed statistically based on the maximum, mean and minimum values, along with the standard deviation. Moreover, it is observed that wind power conversion system is economical within certain range of wind velocity. On the other hand, WPCS has greater impact on emission of pollutants. The suggested methods deliver results of scheduled outputs of available generators with the inclusion of wind power. The incorporation of the variable cost of the wind generator along with the conventional thermal generators has proved to be fruitful in the objective of cost minimization. Time complexity can be improved of HSOA.

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