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MULTI-OBJECTIVE BASED ECONOMIC EMISSION DISPATCH PROBLEM IN THERMAL-WIND SYSTEM USING IFOA TECHNIQUE

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Abstract— This paper proposed a multi-objective based hybrid methodology to understand Economic Emission Dispatch (EED) issue coordinates wind power with thermal units. The mixture approach is the joined execution of both the Improved Fruit Fly Optimization Algorithm (IFOA) and Artificial Neural Network (ANN) system. In this work, the IFOA is used for optimizing the blend of the thermal generators in view of the wind power vulnerability. The ANN is used to catch the vulnerability occasions of wind power to the system is guaranteed the high use of wind power. Accordingly, a solution of the proposed optimization approach is limited the total fuel cost and emission cost. To approve the proposed strategy viability, the six generating units thermal system is considered with fuel and emission cost as two clashing targets to be upgraded in the meantime. The proposed strategy is executed in MATLAB working platform and the outcomes are inspected with thinking about generation units and which is contrasted and different solution procedures. The comparison happens uncovers the nature of the proposed approach and broadcasts its capacity for dealing with multi-objective optimization problems of power systems.

Keywords— Economic Emission Dispatch, wind power generator, thermal generators, IFOA, ANN, Multi-objective optimization

I. INTRODUCTION

Huge research has been led all through the world for improvement of manageable, renewable and productive energy systems keeping in mind the end goal to meet the necessities of the expanded populace and to diminish the broad utilization of fossil fuels [1]. Expanding energy costs, environmental concerns and rapid depletion of the known fuel saves have essentially expanded the extent of renewable energy sources (RES). RES are utilized in the networks of the power system to meet environmental, economic, industrial, and community level needs [2]. As of late, the wind power, solar and thermal power pulled into much consideration like promising renewable energy resources [3]. The energy resources have different attributes regarding operational costs and unwavering quality. Wind energy generation has changed into an elective source of energy for the customary resources [2]. On account of the wind irregularity and eccentrics, the infiltrations of wind power have extended, more imaginative and refined systems are grasped in the planning of existing creating limit, strategies and operating protocols [4, 5].

Despite the fact that its power generation minor cost is zero along these lines, WEGS forces an additional weight of costs on the power system [6]. Alongside the extra holds coordination to ensure a dependable and economical power supply, auxiliary administrations ought to be booked appropriately [7]. The economic and environmental issues in the power generation have gotten impressive consideration. Economic Dispatch (ED) is an indispensable and most continuous advance in power system operational arranging [8]. ED is an optimization issue that distributes power to each dedicated creating unit in order to limit the total operational cost, subject to constraints. Different constraints incorporate power balance, power limits of generators, restricted working zones, ramp rate limits and so forth. the issue is figured as a multi-objective optimization problem [10, 11]. It comprises in dispersing the active and renewable preparations between the power stations of the most economic route, to decrease the emissions of the contaminating gases and to keep up the security of the network after infiltration of renewable energy. The number of choice factors of the issue is identified with every one of the nodes of the network. A few optimization methods with equality and inequality constraints have been utilized for ED. The optimization methods are PSO [14], Tabu Search [17], Sequential Quadratic Programming (SQP), Enhanced PSO (EPSO) [16], Artificial Bee Colony (ABC) [12, 13], Genetic Algorithm (GA) [9], Hybrid Shuffled Differential Evolution (SDE) [15]], Neural Network [18, 19] et cetera. All above-said systems can take care of EED issue, however, a number of samples required are huge and consequently the unpredictability of the algorithm is sufficiently high so as not to enable it to work in real-time [20].

In this paper, a multi-objective based hybrid methodology of IFOA with ANN is used to solve EED (Economic Emission Dispatch) problem in power system. The proposed technique is clearly described in detail. The remainder of this article is organized as follows; the recent research work and the background of the research work are discussed in Section 2. The proposed technique thorough explanation is explained in Section 3 and 4. The suggested technique achievement results and the related discussions are given in Section 5 and the paper is concluded in Section 6.

II. Recent Research Works: A Brief Review

Several research works have previously existed in the literature which was based on the unit commitment with the renewable system using various techniques. Some of the works are reviewed here.

V. K. Jadoun et al. [21] have clarified the stochastic nature of wind and solar was demonstrated by Weibull and beta distributions, separately. Additionally, economic Optimization was acquired by a recently created algorithm called Improved Fireworks Algorithm with the non-uniform operator (IFWA-NMO). This presents adaptive dimension strategy, limiting mapping operator and non-uniform operator. The adequacy of proposed IFWA-NMO was examined on the standard Dynamic Economic Load Dispatch (DELD) system and furthermore utilized to understand conventional dead with the wind-solar system. M. Kheshti et al. [22] have built up a utilization of another proposed Double Weighted Particle Swarm Optimization (DWPSO) system in illuminating Non-convex Combined Emission Economic Dispatch (CEED) issues with wind power infiltration. Likewise, the systems used to explaining the non-convex multiple fuel option economic dispatch issue have been mechanically exhibited. DWPSO effectively decreases the creation costs and risky emissions considering wind power infiltration, chooses the best fuel kinds of the generators and alters the practical and ideal settings to apportion load demand to the online age units in power system. To take care of the CEED issue of the microgrid considering the solar and wind power cost functions the Modified Harmony Search (MHS) algorithm was built up by W. E. Elattar et al. [23]. The introduced algorithm was inferred by modifying the parameters as well as enhancing the structure and operation of the first harmony search (HS) algorithm. The solution of the CEED issue of the microgrid considering the solar and wind power cost functions was acquired for various situations utilizing the MHS algorithm and some as of late distributed algorithms. For upgrading the economic dispatch issue, another algorithm was found by C. Shilaja et al. [24]. The new algorithm depended on CEED for photovoltaic (PV) plants and thermal power generation units. In CEED approach for extemporizing the economic dispatch Euclidean affine flower pollination algorithm (eFPA) and Binary Flower Pollination Algorithm (BFPA) have been utilized for taking care of the optimization issue for twenty PV and five thermal generators were finished with full solar radiations and with lessened solar radiation.

Multi-objective economic emission power dispatch issue plan and arrangement incorporating stochastic wind, solar and small-hydro (run-of-river) power was talked about by P. P. Biswas et al. [25]. Weibull, lognormal and Gumbel probability density functions were utilized to compute accessible wind, solar and small-hydro power respectively. Some conventional generators of the standard IEEE 30-bus system were supplanted with renewable power sources for ponder reason. R. M. Rizk-Allah et al. [26] illustrated a parallel hurricane optimization algorithm (PHOA) for understanding economic emission load dispatch (EELD) issue in present-day power systems. In PHOA, a few sub-populations moving freely in the search space with the point of all the while optimize the issue objectives thinking about the neighborhood conduct between sub-populations. By along these lines, it was proposed to scan for the Pareto optimal solutions that were in contrast to the single optimal solution. The inborn attributes of parallelization strategy can improve the Pareto solutions and increment the union to achieve the Pareto optimal solutions. A. A. Elsakaan et al. [27] have been depicted an Enhanced Moth-Flame Optimization (EMFO) algorithm for illuminating the non-convex ED issue with valve-point impacts and emissions. It decides the optimal generation timetable of producing units by limiting both fuel cost and emission cost of the system constraints were accomplished. The Moth-Flame Optimization (MFO) was an ongoing nature-inspired strategy, which depended on the navigation mechanism called transverse orientation of moths in space. The EMFO joins the benefits of the customary MFO and levy flight by focus the search space. The utilization of lévy-flight have the noticeable properties to expand the assorted variety of population.

A. Background of the Research Work

ED with renewable energy plays a significant role since the problem depends on the operating cost of the generation units. The review shows that the formulation of economic dispatch problem with renewable energy is directly improving the solution methodology. In renewable energy, wind power is sustained more in power system. For that reason, the unit commitment problem is a complicated and more challenging task because of the uncertainty power generation of the wind energy system. Therefore, the multi-objective optimization is formed as a problem with uncertainty. Different methods are used to accommodate wind and solar power variability including advanced unit commitment and balancing wind and solar power variations. The purpose of this model has improved the formulated model by considering wind power uncertainty will lead to a better solution which can withstand the estimate errors in the real time. Numerous methods are available to solve the unit commitment problem such as improved fireworks algorithm with the non-uniform operator (IFWA-NMO), modified harmony search (MHS) algorithm, Euclidean Affine Flower Pollination Algorithm (eFPA), Binary Flower Pollination Algorithm (BFPA), Enhanced Moth-Flame Optimization (EMFO) and so on. But those methods only concentrate the thermal generation into account and did not consider the impact of wind power uncertainty. In the literature, very few works are presented to solve this problem and the drawbacks of the work have motivated to do this research work.

III. Proposed Thermal-Wind Based Economic Emission Dispatch

In this paper, the hybrid methodology is proposed for reducing the economic and emission dispatch problem of the renewable energy system. The hybrid methodology is the combination of both the improved fruit fly optimization algorithm (IFOA) and artificial neural network (ANN). In light of the wind power uncertainty, the IFOA is optimizing the combination of the thermal generators. By the probability occurrence of wind power and production cost of thermal units, the multi-objective function will be formed. ANN will be used to predict the uncertainty events of wind power. Here, the generation scheduling involving planned outputs of thermal, and wind power units is the main goal for the EED problem [26]. The fuel cost and emission cost of the electrical power system can be minimized by this generation scheduling accomplished by the scheduling period given to the various equality and inequality constraints. The problem formulation of the EED model for wind and thermal power is derived as follows,

A. Multi-Objective Formulation of EED

The EED multi-objective function minimizes the operating cost such as fuel cost and start-up cost of the generating units by considering the wind power and thermal units. Here, the wind power generation and thermal unit's allocations are the major problems. Since the wind power depends on nature and the thermal unit's allotments are possible only at the peak hours, the wind power is designed as the probability function. According to the wind availability, the operational costs of the thermal generators are reduced. The Multi-objective function of the EED model for thermal and wind power considered is given as follows (1).

$$\Phi = Min\,[F_{TC}] \tag{1}$$

Here, F_{TC} is the total cost that can be described as in equation (2).

$$F_{TC} = \sum_{t=1}^{H}\sum_{i=1}^{N}\left[f_c\left(P_{TG}(i,t)\right)U(i,t) + SC(i,t)\right] \times prob_{WT}(j,t) \tag{2}$$

Where $f_c\left[P_{TG}(i,t)\right]$ indicates the fuel cost of the thermal generating units ($). H stand for the total number of hours. $U(i,t)$ is the status of the unit i at t^{th} hour, i.e., '1' for ON and '0' for OFF. $SC(i,t)$ denotes the start-up cost of the unit i at t^{th} hour and $prob_{WT}(j,t)$ is the probability of the wind generator unit j at t^{th} hour. The fuel cost and the start-up cost evaluation is described in the following equation (3).

$$f_c\left[P_{TG}(i,t)\right] = a_i + b_i P_{TG}(i,t) + c_i P_{TG}^2(i,t) \tag{3}$$

Recommended font sizes are shown in Table 1.

B. Wind Power Formulation

The stochastic variable wind speed (m/s) is utilized to decide the yield energy of a wind generator. For the most part, it is trusted that two parameter of Weibull probability density Function (PDF) the technique has a specific level of exactness in wind speed displaying. Here, for the utilization in the EED issue, the Weibull PDF [27, 28] for wind speed is accepted and after that changed to wind control conveyance framework. The speed v (m/s) for the Weibull PDF $f(v_s)$ is given as,

$$f(v_s) = (h/c)(v/c)^{h-1}\exp\left[-(v/c)\right], \quad v \ge 0 \tag{4}$$

The corresponding Cumulative Distribution Function (CDF) $F(v_s)$ is derived based on the Weibull PDF is represented as follows,

$$F(v_s) = 1 - \exp\left[-(v/c)^h\right] \tag{5}$$

Where, $f(v_s)$ and $F(v_s)$ are the PDF and CDF respectively. c and k are the two positive numbers known as the scaling factor and the shape factor separately. The output power of the wind generator and the speed of wind are related as,

$$P_w = \begin{cases} 0, & v < v_{cin}\ or\ v > v_{cout} \\ P_r \dfrac{v - v_{cin}}{v_r - v_{cin}}, & v_{cin} \le v < v_r \\ P_r\,, & v_r \le v \le v_{cout} \end{cases} \tag{6}$$

Where, P_r and v_r are the rated output power and rated wind speed while v_{cin} and v_{cout} are the cut-in and cut-out speed of the wind respectively. At that point when the wind speed is between the rated and the cut-out wind speed, the yield of the wind generator is in working condition. When the wind speed is within the range of cut-in and cut-out speed, P_w is in non zero condition. P_w is in the range of [0, P_r] for CDF can be formulated as,

$$F(P_w) = 1 - \exp\left\{\left[\left(1 + \frac{V_r - V_{cin}}{V_{cin} P_r} \cdot P_w\right) \frac{V_{cin}}{c}\right]^h\right\} + \exp\left[-\left(\frac{V_{cout}}{c}\right)^h\right], \quad 0 \le P_w < P_r \tag{7}$$

For formulating the model of economic emission dispatch problems, the equation (7) is important since it has the stochastic wind power.

C. Thermal Power Formulation

1) Fuel Cost of Thermal Power Generation: In a power system, the thermal plant generation cost is considered as fuel cost during the scheduling period [29]. The thermal power output with a quadratic function is formulated as,

$$F_f = Min\left[\sum_{i=1}^{N_{Ti}}\left[x_i + y_i P_{Ti} + z_i P_{Ti}^2 + \left|p_i \sin\left(q_i\left(P_{i,\min} - P_{Ti}\right)\right)\right|\right]\right] \tag{8}$$

Where F_f speaks for fuel cost objective of the thermal power system, P_{Tit} represents the power generated at a time t in i^{th} the thermal unit, T represents the total dispatch period length, x_i, y_i, z_i, p_i, q_i represents the i^{th} thermal unit coefficients of fuel cost, $P_{i,\min}$ indicates the minimum output of i^{th} the thermal unit, N_{Ti} is the number of thermal plants.

2) Emission Cost of Thermal Power Generation: The total polluting emissions of thermal power generation takes into consideration the release of harmful gases like NO_x, SO_2. The thermal power output of total emission cost is based on the sum of quadratic and exponential functions and it can be derived as follows:

$$F_e = Min\left[\sum_{i=1}^{N_{Ti}}\left[a_i + b_i P_{Ti} + c_i P_{Ti}^2 + d_i \exp\left(e_i \cdot P_{Ti}\right)\right]\right] \tag{9}$$

Where, F_e represents the emission cost of the thermal power system and a_i, b_i, c_i, d_i, e_i represents the i^{th} thermal unit coefficients for emission cost.

D. Constraints of the System

The system constraints have stochastic characteristics due to the presence of wind power generators [30]. The constraints can be satisfied at a pre-defined confidence level by the form of probability and the addition of stochastic variables.

1) Constraints of Power Balance: The total power generated from the different types of sources like the thermal generating unit and wind power generating unit at each hour must be equal to the load of the corresponding hour. This constraint is explained in the following equation (10).

$$P_{TD}(t) = \sum_{i=1}^{n} P_{TG}(i,t) U(i,t) + P_{WT}^{NN}(j,t) \tag{10}$$

Where, $P_{TD}(t)$ is the total demand at period t; $P_{TGi}(i,t)$ is the power generated from the thermal unit i at the hour t; $P_{WT}^{NN}(j,t)$ is the power generated from the wind unit j at hour t, which is attained from the ANN.

2) Constraints of Thermal Unit: The thermal generating system consists of different types of constraints such as generation capacity, minimum uptime and minimum downtime of the generators and ramp generation, which are described as follow.

(i). Generating capacity constraints [28]

$$P_{TG}^{\min}(i,t) \le P_{TG}(i,t) \le P_{TG}^{\max}(i,t) \tag{11}$$

(ii). Minimum uptime limit [28]

$$T_{on}(i,t) > Min\, up(t) \tag{12}$$

(iii). Minimum downtime [28]

$$T_{off}(i,t) > Min\, down(t) \tag{13}$$

(iv). Ramp generation [30]

$$P_{TG}(i,t) - P_{TG}(i,t-1) \le RU(i) \quad \text{as generation increases} \tag{14}$$

$$P_{TG}(i,t) - P_{TG}(i,t-1) \le RD(i) \quad \text{as generation increases} \tag{15}$$

Where, $P_{TG}^{\min}(i,t)$ and $P_{TG}^{\max}(i,t)$ are the minimum and maximum power of thermal generating unit i at t^{th} hour; $Min\,up(t)$ is the minimum uptime of thermal generating unit at t^{th} hour; $Min\,down(t)$ is the minimum downtime of thermal generating unit at t^{th} hour; $T_{on}(i,t)$ is duration at which thermal generating unit i has been on at t^{th} hour; $RU(i)$ and $RD(i)$ are the ramp up and down limit of the unit i. These multi-objective EED problems are solved by the hybrid IFOA and ANN approach. Both the IFOA and ANN approaches are clearly depicted in the section beneath.

IV. HYBRID IFOA AND ANN APPROACH FOR EED PROBLEM

To eliminate the EED problems, the proposed work utilized the IFOA and ANN hybrid approach. Here, the IFOA is used to optimize the combination of generation. Here, the crossover and mutation are used to modify the searching behavior of the fruit fly swarm. ANN will be used to predict the uncertainty events of wind power. The clear description of the proposed technique is illustrated in the following section.

A. IFOA for Combination of Generation Optimization

The IFOA is a novel method for searching global optimization. It originated from the research on food hunting behaviors of fruit fly swarm. The fruit fly is an excellent food hunter with sharp vision [31]. In IFOA, to better balance exploitation and exploration, the parallel search is adopted. In addition, aiming to make full use of swarm intelligence, the searching behavior of the fruit fly is modified by using the efficient neighborhood search functions like crossover and mutation to add communication among swarms in IFOA. In light of the wind power uncertainty, the IFOA is optimizing the combination of the thermal generators. By the probability occurrence of wind power and production cost of thermal units, the multi-objective function is formed. The IFOA strategy is examined beneath.

B. Steps of IFOA

Step-1: Initialization of fruit fly swarm location

Initialize the economic and emission coefficients, power limits of generators, wind power at an instant time and load demand. The random generation of power value combination is initialized as P_{random}. The randomly generated position of fruit fly can be represented as,

$$P_{random} = random\ (H - L) + L \tag{16}$$

Where, H and L are the higher and lower bounds respectively, random is the random numbers uniformly generated in the range of 0-1.

Step-2: Start loop: Set Generation = 1

Perform operations on randomly generated population vector to get best population vector. Operations to be performed are listed below.

Step-3: Osphresis foraging phase

Minimizing the power variation of the thermal generation unit is the objective function of the proposed method and this can be done in the foraging phase. The following function indicates the objective function of the proposed technique.

$$Fitness\ \ Function = Min\ \{F_M\} \tag{17}$$

Where, F_M the multi-objective function is formulated for the economic emission dispatch problem of the thermal generating unit. Based on the balanced constraints of the system, the fitness function of the system is calculated.

Step-4: Crossover and Mutation

It is an efficient recombination operator has been used to search swarm food location in certain long range. Recombination crossover and mutation generates new swarm locations by using the following crossover and mutation equation.

$$Crossover = \frac{N_{Genes-crossovered}}{L_{chromosome}} \tag{18}$$

$$Mutation = \frac{M_p}{L_{chromosome}} \tag{19}$$

Where, $N_{Genes-crossovered}$ indicates the number of genes crossover, M_p represents the mutation point and $L_{chromosome}$ indicates the length of the fruit fly.

Step-5: Vision foraging phase

In this phase, fruit fly optimization carries a greedy selection procedure. Finding the best food source with the lowest fitness was given by,

$$X_{best} = \arg(\min F_m), \quad m = 1,2,...,n \tag{20}$$

If X_{best} is better than the current fruit fly swarm location, the fly will replace the new position. Otherwise, swarm location will not change.

Step-6: Stopping criteria

Stop the process, if the maximum number of generations is reached. Otherwise, go to step 2 and repeat the process up to the specified maximum number of generations. Here we set the maximum of generations is 100.

C. ANN for Wind Power Generation Prediction Process

To optimize the wind speed and to predict the best speed factor of the wind, the ANN is utilized. Wind speed is taken as the input of the network and the wind probability is the output of the network. During the learning process, the non-linear function of the input is outputted and is controlled by weights which are computed. The ANN is used to capture the uncertainty events of wind power to the system ensures the high utilization of wind power. Therefore, a solution of the proposed optimization approach is minimized the total cost by using the backpropagation learning algorithm [32].

Backpropagation learning algorithm steps

Step 1: Initialization of the input layer, hidden layer and output layer weights of the neural network, i.e., day (D), hour (H), wind speed $S_{WT}(j,t)$ and wind power generation $P_{WT}(j,t)$.

Step 2: Learning the network according to the input and the corresponding target.

Step 3: Calculate the back propagation error of the target $P_{WT}(j,t)_1, P_{WT}(j,t)_2$ *and* $P_{WT}(j,t)_k$.

$$\left.\begin{aligned} BP_{error}^{1} &= P_{WT}(j,t)_1^{NN(tar)} - P_{WT}(j,t)_1^{NN(out)} \\ BP_{error}^{2} &= P_{WT}(j,t)_2^{NN(tar)} - P_{WT}(j,t)_2^{NN(out)} \\ BP_{error}^{k} &= P_{WT}(j,t)_k^{NN(tar)} - P_{WT}(j,t)_k^{NN(out)} \end{aligned}\right\} \tag{21}$$

Where, $P_{WT}(j,t)_k^{NN(tar)}$ is the network target of the k^{th} node and $P_{WT}(j,t)_k^{NN(out)}$ is the current output of the network.

Step 4: The current output of the network is determined by using the following equation,

$$\left.\begin{aligned} P_{WT}(j,t)_1^{NN(out)} &= \alpha_1 + \sum_{n=1}^{N} w_{1n}\, P_{WT}(j,t)_1^{NN}(n) \\ P_{WT}(j,t)_2^{NN(out)} &= \alpha_2 + \sum_{n=1}^{N} w_{2n}\, P_{WT}(j,t)_2^{NN}(n) \\ P_{WT}(j,t)_k^{NN(out)} &= \alpha_k + \sum_{n=1}^{N} w_{kn}\, P_{WT}(j,t)_k^{NN}(n) \end{aligned}\right\} \tag{22}$$

Where, α_1, α_2 and α_k are the bias function of the node $1, 2\, and\, k$ respectively.

$$\left.\begin{aligned} P_{WT}(j,t)_1^{NN}(n) &= \frac{1}{1+\exp(-w_{1n}P_{WT}(j,t)_1 - w_{2n}P_{WT}(j,t)_2)} \\ P_{WT}(j,t)_2^{NN}(n) &= \frac{1}{1+\exp(-w_{2n}P_{WT}(j,t)_2 - w_{kn}P_{WT}(j,t)_k)} \\ P_{WT}(j,t)_k^{NN}(n) &= \frac{1}{1+\exp(-w_{kn}P_{WT}(j,t)_k - w_{1n}P_{WT}(j,t)_1)} \end{aligned}\right\} \tag{23}$$

$$\left.\begin{aligned} \Delta w_1 &= \delta . P_{WT}(j,t)_1 . BP^1_{error} \\ \Delta w_2 &= \delta . P_{WT}(j,t)_2 . BP^2_{error} \\ \Delta w_k &= \delta . P_{WT}(j,t)_k . BP^k_{error} \end{aligned}\right\} \tag{24}$$

Step 5: The new weights of each neuron of the network are updated by $w_{new} = w_{old} + \Delta w$. Here, w_{new} is a new weight, w_{old} is the previous weight and Δw is the change of weight of each output. The change of weight is determined as follows:

Where, δ is the learning rate (0.2 to 0.5).

Step 6: Repeat the above steps until the BP_{error} gets minimized $BP_{error} < 0.1$.

Once the neural network training process is completed, the network is trained well for the identifying $P^{NN}_{WT}(j,t)$.

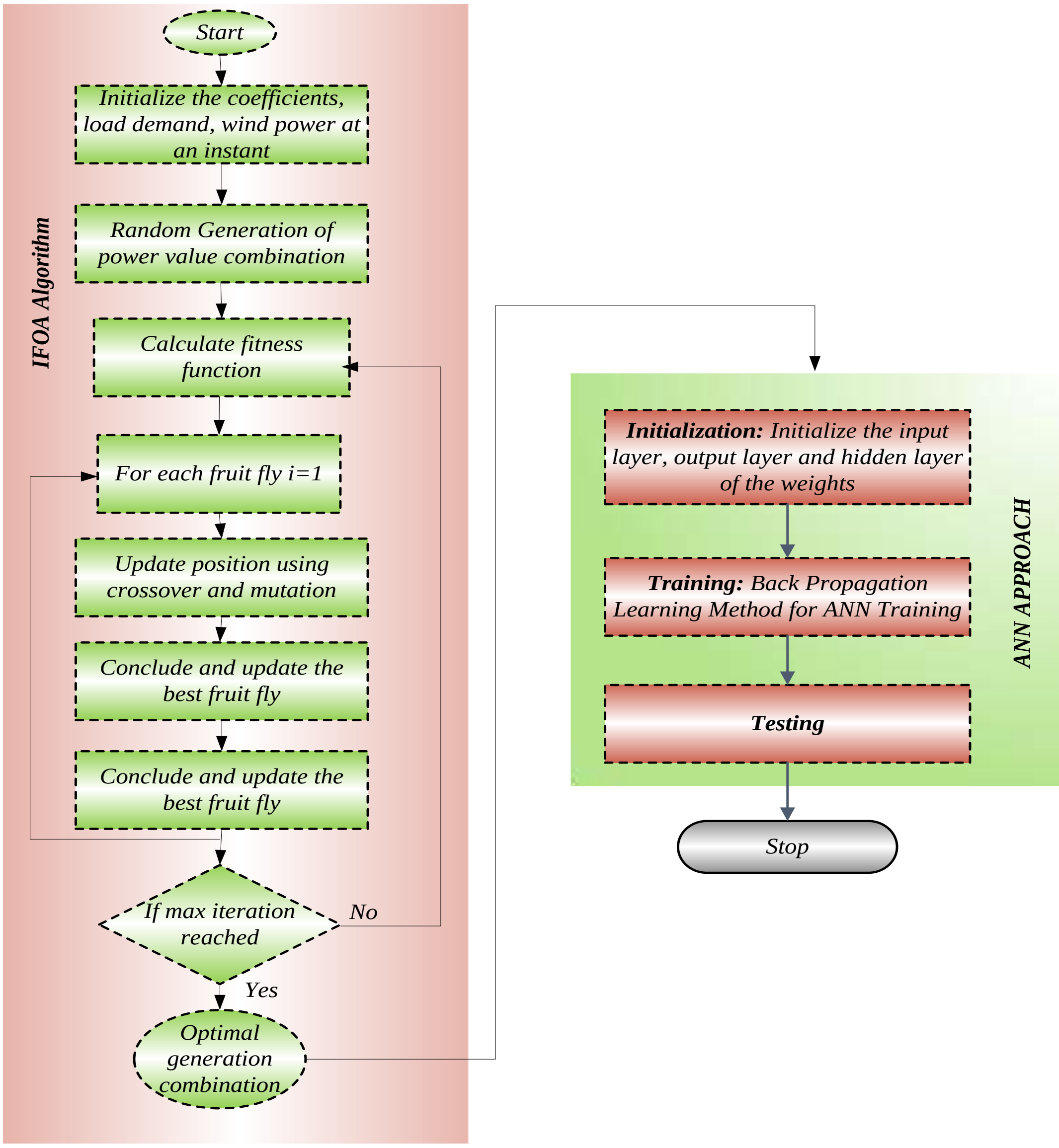

Fig. 1 Flowchart of the Proposed IFOA-ANN Approach

V. RESULTS AND DISCUSSIONS

In this segment, the proposed technique results are presented and the different existing algorithms are compared with the proposed method. The comparison of the proposed with the existing techniques has been implemented in the MATLAB/simulation working stage in order to show the effectiveness of the proposed approach [33]. Individually fuel cost and emission objectives are minimized by utilizing the proposed strategy. To solve the optimization by with and without using wind power generation for 24 hours, a six-unit generating system is taken and their results are compared with different techniques.

TABLE 1
LOAD DEMAND, FUEL AND EMISSION COST OF 6 UNIT SYSTEM FOR DIFFERENT HOURS WITHOUT WIND POWER.

Generators	**Unit 1**	**Unit 2**	**Unit 3**	**Unit 4**	**Unit 5**	**Unit 6**	**Demand**	**Fuel Cost ($)**	**Emission Cost ($)**
P_{G1}(MW)	25.5	104.5	42.5	39.5	128.53	159.57	500	28456.08	114.07
P_{G2}(MW)	25	35	50	163	126	151	550	29728.71	145.01
P_{G3}(MW)	105.83	132.83	188.83	200.83	312.83	308.83	1250	65009.73	1077.14
P_{G4}(MW)	74.83	127.83	187.83	214.83	277.83	316.83	1200	61954.19	1008.07
P_{G5}(MW)	98	75	197	212	222	296	1100	56546.92	834.28
P_{G6}(MW)	117.66	110.66	204.66	223.66	278.66	314.66	1250	64913.41	1087.97

The proposed approach for the six-unit generating system is discussed below. In this experiment, a 6 unit generating thermal system is contemplated. The generation, fuel cost and emission cost of the 6 generating units for 24 hours is computed and contrasted and the differing power demand. Table 1 demonstrates the compressed consequences of the 6 generator system for six diverse load demands like 500, 550, 1250, 1200, 1100 and 1250 at five distinct hours. The outcomes are acquired by the proposed technique without utilizing the wind power generation and the relating fuel cost and emission costs are examined. Generation and the relating fuel cost, and emission cost are examined. Also, Table 2 demonstrates the after-effects of the 6 generator systems for six diverse load demands at five unique hours by utilizing the wind power generation. Table 1 and 2 obviously demonstrates that the fuel cost and emission cost of the 6 generator system give better outcome while fulfilling the generator's yield requirements.

TABLE 2
GENERATION, LOAD DEMAND, FUEL AND EMISSION COST OF 6 UNIT SYSTEM FOR DIFFERENT HOURS WITH WIND POWER

Generator	**Unit 1**	**Unit 2**	**Unit 3**	**Unit 4**	**Unit 5**	**Unit 6**	**Wind Power**	**Demand**	**Fuel Cost ($)**	**Emission Cost ($)**
P_{G1}(MW)	40.54	15.54	36.54	42.54	128.53	148.54	77.70	500	23800.55	46.63
P_{G2}(MW)	47.27	18.27	102.27	58.27	126.27	136.27	61.35	550	26758.37	62.75
P_{G3}(MW)	50.01	109.01	157.01	217.01	296.01	316.01	104.90	1250	58584.95	948.42
P_{G4}(MW)	105.50	108.50	157.50	221.50	233.50	263.50	109.97	1200	56726.63	779.82
P_{G5}(MW)	29.37	71.37	170.37	139.37	287.37	286.37	115.72	1100	49964.43	684.02
P_{G6}(MW)	80.79	115.79	139.79	182.79	302.79	323.79	104.24	1250	58972.13	917.89

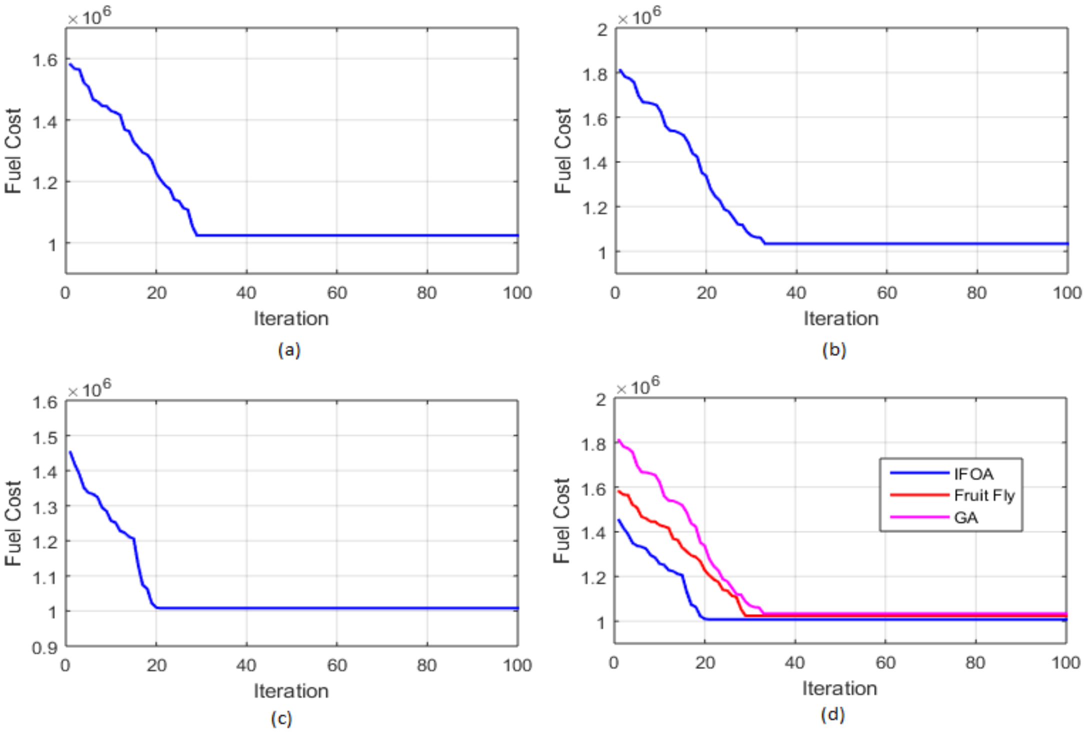

Fig. 2 Fuel Cost Comparison With Wind Power (a) Fruit Fly (b) GA (c) Proposed IFOA (d) Comparison of the fruit fly, GA, and IFOA

Figure 2 demonstrates the fuel cost of the proposed IFOA method with wind power generation system which is compared with the existing methods such as Fruit Fly Optimization Algorithm (FOA) [34] and the Genetic Algorithm (GA) [35]. The fuel cost union diagram of 6 unit generating system in terms of emphases are clearly depicted in that figure. Here, the subplot (a) illustrates the fuel cost of the FOA, subplot (b) illustrates the fuel cost of the GA, and subplot (c) illustrates the fuel cost of the IFOA. The comparison results of all the FOA, GA, and the IFOA is illustrated in subplot (d). the proposed IFOA method has the less fuel cost when compared with the existing FOA, and the GA algorithm. The fuel cost of the wind power system is varied with respect to the iteration range. In the FOA algorithm, the fuel cost is 1.6×10^6 at the 0^{th} level iteration and in the 30^{th} iteration, the cost is reduced (1×10^6) and it goes constantly till the end of the operation. In the GA algorithm, the fuel cost is 1.8×10^6 at the 0^{th} level iteration and in the 34^{th} iteration, the cost is reduced (1×10^6) and it goes constantly till the end of the operation. In the proposed IFOA algorithm, the fuel cost is 1.45×10^6 at the 0^{th} level iteration and in the 20^{th} iteration, the cost is reduced (1×10^6) and it goes constantly till the end of the operation.

Fig 3 demonstrates the emission cost of the proposed IFOA method with wind power generation system which is compared with the existing methods such as Fruit Fly Optimization Algorithm (FOA) and the Genetic Algorithm (GA). The emission cost union diagram of 6 unit generating system in terms of emphases are clearly depicted in that figure. Here, the subplot (a) illustrates the emission cost of the FOA, subplot (b) illustrates the emission cost of the GA, and subplot (c) illustrates the emission cost of the IFOA. The comparison results of all the FOA, GA, and the IFOA is illustrated in subplot (d). the proposed IFOA method has the less emission cost when compared with the existing FOA, and the GA algorithm. The emission cost of the wind power system is varied with respect to the iteration range. In the FOA algorithm, the emission cost is 1.32×10^4 at the 0^{th} level iteration and in the 30^{th} iteration, the cost is reduced (1.13×10^4) and it goes constantly till the end of the operation. In the GA algorithm, the emission cost is 1.42×10^4 at the 0^{th} level iteration and in the 34^{th} iteration, the cost is reduced (1.15×10^4) and it goes constant till the end of the operation. In the proposed IFOA algorithm, the emission cost is 1.18×10^4 at the 0^{th} level iteration and in the 24^{th} iteration, the cost is reduced (1.07×10^4) and it goes constant till the end of the operation.

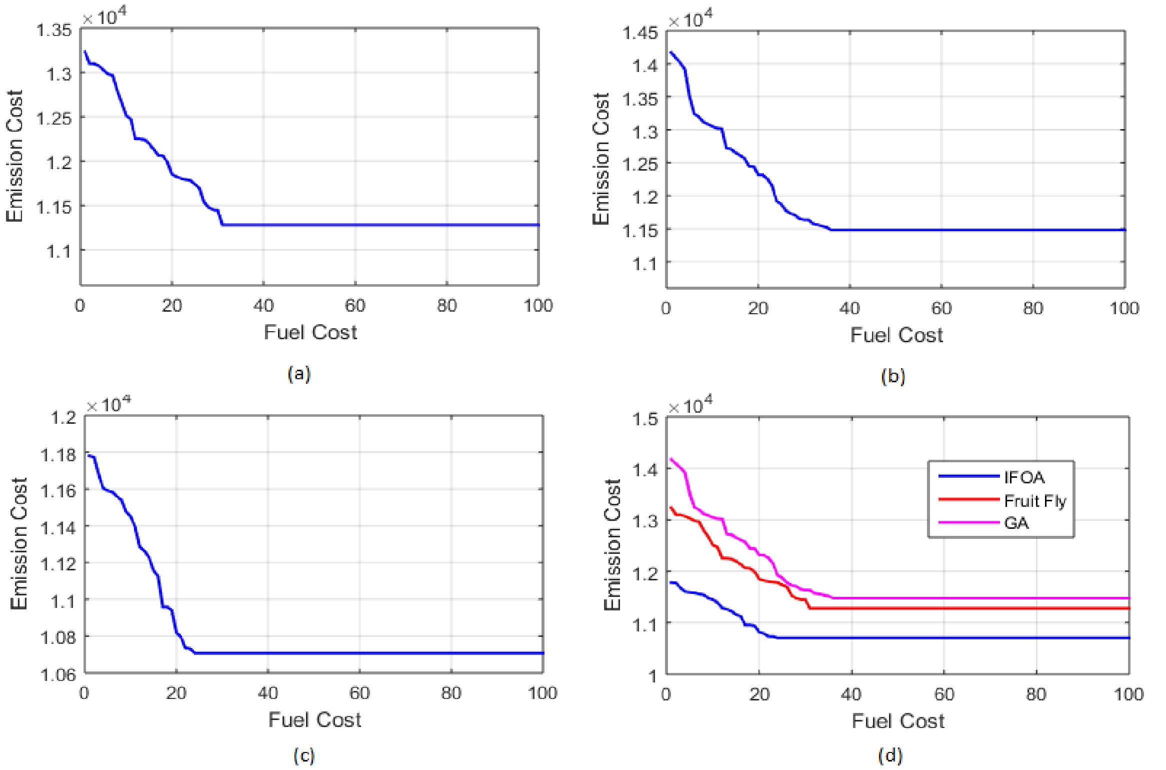

Fig. 3 Emission Cost Comparison with Wind Power (a) Fruit Fly (b) GA (c) Proposed IFOA (d) Comparison of the fruit fly, GA, and IFOA

TABLE 3
COMPARISON OF FUEL COST AND EMISSION COST WITHOUT WIND POWER

Without Wind Fuel Cost			
Method	**Mean x 10^6**	**Median x 10^4**	**Std.Dev x 10^6**
IFOA	1.1356	1.3613	1.1493
Fruit fly	1.1371	1.3872	1.1510
GA	1.1383	1.3871	1.1522
Without Wind Emission Cost			
IFOA	1.0080	1.0707	1.0187
Fruit fly	1.0241	1.1281	1.0354
GA	1.0339	1.1477	1.0453

TABLE 4
COMPARISON OF FUEL COST AND EMISSION COST WITH WIND POWER

With Wind Fuel Cost			
Method	**Mean x 10^6**	**Median x 10^4**	**Std.Dev x 10^5**
IFOA	1.0550	1.0080	1.1003
Fruit fly	1.1113	1.0241	1.6247
GA	1.1590	1.0339	2.2987
With Wind Emission Cost			
IFOA	1.0839	1.0707	2.9120
Fruit fly	1.1572	1.1281	5.4243
GA	1.1847	1.1477	6.9123

Table 3 delineates statistical comparison amongst proposed and diverse calculations for 6-generating units in terms of mean, median, the standard deviation of the fuel, and emission cost without wind generation system which are related with the 6 generator power system. Likewise, Table 4 delineates the statistical comparison amongst proposed and diverse calculations for 6-generating units in terms of mean, median, the standard deviation of the fuel, and emission cost with wind generation system which are related with the 6 generator power system. The mean, median and the standard deviations of the proposed IFOA method is compared with the existing methods such as FOA and GA. It obviously demonstrates that the proposed technique gives lesser estimations of fuel and emission cost for both with and without utilizing wind power generation when contrasted and the different calculations. The statistical comparison amongst proposed and diverse calculations for 6-generating units in terms of mean, median, standard deviation. When compared with the existing methods, the proposed IFOA method has a better mean, median, and the standard deviation values.

VI. CONCLUSIONS

In this paper, for deciding the EED issue of the thermal-wind unit, IFOA with AI method is proposed. At first, the issue has been systemized as the multi-objective optimization with clashing fuel cost and environmental emission objectives. For limiting the fuel and emission cost of the thermal system with the anticipated wind speed factor, the proposed cross breed strategy is used. The proposed strategy is realized in MATLAB working platform and the results are analyzed with thinking about generation units and it is contrasted and different solution procedures. The performances of the proposed strategy are explored on six generating units of the thermal system with and without utilizing wind power generation. The statistical analysis of six generating units of thermal system is contrasted and different algorithm concerning best cost, worst cost, mean, median and standard deviations separately. The examination demonstrates that the proposed procedure is more successful than the other solution methods for tackling the EED issue notwithstanding for large-scale power systems. Likewise, the proposed system yields an aggressive execution as far as the solution. Along these lines, the proposed strategy is a promising procedure for deciding confounded issues and gives off an impression of being a strong and effective technique for taking care of multi-objective optimization issues in power system.

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