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Solving Economic Load Dispatch Problem with Integrated Renewable Resources: A Comparative Analysis on Optimization Algorithms

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Abstract: - The classical Economic Load Dispatch (ELD) problem deals with the exploration of solution to the optimal active power allocation from all the sources to minimize the total operating cost, while satisfying the load demand. In this work, an analytical evaluation is undergone with diverse standard optimization algorithms on providing solution to ELD problem under multi-objectives like total wind generation cost, total cost function of thermal units and the penalty cost function. In addition, the optimization algorithms play a major role in optimizing power generation of thermal power plant within the maximal and the minimal bounds, and the selection of wind turbine in wind power system to meet the power demands with utmost efficiency. Finally, an evaluation is done with diverse optimization on IEEE-14 and IEEE-30 bus system to explore solutions to the aforementioned optimal selections.

Keywords—Power Generation; Wind Power; Economic load dispatch; Mult-objective Problem; Optimization Algorithm

I. INTRODUCTION

Recently, different rivalry and ideal changes are being undergone in the field of the power generation, owing to the opening of the energy division. At that point, the a greater commitment is highly discussed by the distributed generation in the entire electric power generation of [9] [10] [11] [12]. The modern electric power systems are bulkier in size, distributed geographically and highly interconnected. During the implementation of an electric power system, it is more crucial to have a concern on the effective scheduling of all the generators in order to meet the required system demands. In a practical power system, the allocation of the plants is made with equivalent distance from the load centre and hence the fuel cost tends to vary. Further, in case of normal operations, the capacity of generation is more than the system's total load demand and losses. Therefore, diverse researchers were carried out in generation scheduling. In an interconnected power system, the detection of the "real and reactive power scheduling" for every power plant is the major objective and this helps in minimizing the operating cost of the overall power plant [9] [19] [20] [21] [22]. This means the "real and reactive powers" of the generators are permitted to undergo variation within the stipulated limits to satisfy the system's load demand with reduced fuel cost. This is called ELD problem [13] [14][15] [16] [17].

ELD is a logic where the selection of optimal combination of power generating units is carried out, thereby minimizes the total fuel cost by satisfying several "operational constraints and load demand" as well. The major issue with the most of the power system is they aren't able to satisfy the required power demand of the consumer within the minimal cost. Therefore, the most crucial challenge for power utilities is: balancing of total load among generators and running as efficiently as possible [9] [18] [23] [24] [25].

Diverse conventional methods like LM methods, LI method and N-R method were utilized to solve the problem of ELD. But, owing to the change in the load, it was complex for them to solve the optimal economic problem. Moreover, as the demand was varying, the computation of the ELD each time was complex. Inexhaustible power coordination makes ELD model more complex due to extra imperatives and hence required vigorous optimization algorithm [31] [32] [33] [34] [35] as well to solve these kinds of issues.

The major contribution of this research work is

✓ A solution to ELD is derived by integrating the wind power system with the conventional thermal power generating unit on the basis of multi-objectives like total wind generation cost, total cost function of thermal units and the penalty cost function.

✓ An analysis is made with diverse optimal algorithm to find the best one that aids in generating the thermal power within the maximal and minimal bounds, and turbine selection for efficient power generation based on demand.

The rest of the paper is organized as: Section II addresses the most recent works undergone regarding the load dispatch issues and Section III tells about the economic dispatch problem: integrating the renewable energy system. Further, Section IV portrays about the multi-objective function for optimal ELD. The analysis with diverse optimization algorithm is carried out in Section V and finally this paper is concluded in Section VI.

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II. LITERATURE REVIEW

A. Related works

In 2020, Sengar and Liu [1] have developed MCS-DRNN algorithm with the intention of describing both the optimal design as well as its techno feasibility of the hybrid renewable energy resources like photovoltaic, wind turbine, biogasifiers, and battery. This approach was developed mainly to meet the power demand optimally. The proposed MCS-DRNN approach was the integration of the DRNN and MCS. Further, statistical evaluation was performed to prove the efficiency of proposed approach in terms of both RMSE and MAPE.

In 2019, Suresh *et al.* [2] have presented a new approach for minimizing thermal energy consumption by integrating the DED model and the integrated DR. The DED model encapsulates the shunt FACTS as well as the RESs. In the thermal power plants, the generation cost as well as the peak power consumption was minimized with DR. In the network, the voltage profile was upgraded via the static synchronous compensator (STATCOM and Shunt FACTS device). Further, analyses were carried out by the proposed ADFA.

In 2020, Hamed *et al.* [3] have projected a novel technique with the intention of forecasting the short-term load. This approach was based on the clustering techniques and hybrid models to enhance the quality of the renewable energy in power system grid. The hybrid models of "WNN and ANN, WNN and KF, ANN and WNN, ANN and KF, KF and ANN or KF and WNN" were suggested in this work. As a resultant, the hybrid model of WNN and ANN were finalized as better forecasting model with higher accuracy.

In 2020, Tayab *et al.* [4] have introduced a hybrid approach in a typical microgrid for load demand in the short-term forecasting. This proposed model was based on the amalgamation of the B-BSWPT and HHO-FFNN. In the feed-forward neural, the bias and the weight of the neurons were optimized with Harris hawks optimization. The results have shown the minimization of mean absolute percentage error.

In 2018, Dey *et al.* [5] have proposed a new WOA on an islanded to perform the ELD, emission dispatch as well as CEED and renewable-integrated microgrid. They have evaluated price penalty factor of diverse types and among them, the best price penalty factor was found to form a multi objective approach. As a resultant, there was reduction in the CEED problem with the proposed WOA.

In 2020, Zhao *et al.* [6] have undergone an assessment on ST-EEP of renewable energy power supply in the microgrid. Further, to solve the issues related to reliability of power supply as well as "economy and environmental protection", the author's have developed a QPSO with the help of improved QPSO and DE. As a consequence, the Friedman test has proved with satisfactory results from the proposed model.

In 2019, Wang and Yang [7] have introduced a MAGSO algorithm by merging both the evolution of GSO and the inter individual cooperation of MAS. This approach was developed for large-scale hydropower station to solve the issues in the ELD.

In 2020, Tan *et al.* [8] have proffered a "dispatching model based on renewable energy forecasting errors" with the objective of evaluating the function of existing power supply. They have contributed a "comprehensive forecasting error model", which was developed to "propose wind and PV power forecasting errors into the dispatching system", and the dynamic SR model was constructed on the basis of conditional value at risk. The analyses were carried out at different risk levels. In addition, they have deployed an adaptive analysis approach with the aim of verifying the stability of the renewable energy as well as load demand outcome, even under the presence of additional errors.

B. Review

Table I tabulates the features and challenges of the most fascinating works discussed in the literature. The HMCS-DRNN approach in [1] meets all the electrical requirements in an optimal manner with "minimal error function". But, it produces maximum absolute error. In ADFA [2], there is reduction in operating cost, power loss, and thermal energy consumption cost. Apart from this, the real power loss in the system needs to be reduced significantly. In WNN and ANN deployed in [3], the smallest MAPE and nRMSE error are recorded. But, still the Forecasting errors can be reduced for better performance. The WOA in [5] provides better quality results. Aside from this robustness and capability of the proposed algorithm is lower. The improved QPSO in [6] jumps out of local optimal Solution. Yet, the general costs of the model need to be reduced. In [7], the introduced MAGSO algorithm improved the optimization accuracy. Be as it may be, the convergence rate need to be increased. Further, the A M-OODAA Model in [8], the utilization rate is higher. Yet, the renewable forecasting errors can be diminished.

Nomenclature

Abbreviation	Description
ADFA	Ameliorated Dragonfly Algorithm
ANN	Artificial Neural Network
B-BSWPT	Best-Basis Stationary Wavelet Packet Transform
CEED	Combined Economic-Emission Dispatch
DA	Dragonfly Algorithm
DE	Differential Evolution
DED	Dynamic Economic Dispatch
DR	Demand Response
DRNN	Deep Recurrent Neural Network
EDR	Electricity Demand Reduction
ELD	Economic Load Dispatch

FACTS	Flexible AC Transmission Systems
FF	Fire Fly Algorithm
GSO	Glowworm Swarm Optimization
GWO	Grey Wolf Optimization
HHO-FFNN	Harris Hawks Optimization-Based Feed-Forward Neural Network
KF	Kalman filtering
LI	Lambda Iteration
LM	Lagrange multiplier
MAGSO	Multi-Agent Glowworm Swarm Optimization
MAPE	Mean Absolute Percentage Error
MAS	Multi-Agent System

III. ECONOMIC LOAD DISPATCH PROBLEM: INTERGRATING THE RENEWABLE ENERGY SYSTEM

Over the years, the power systems are becoming complex in response to economic growth and ever expanding demand for power. In the developing countries, due to the industrialization and population increment, more energy is essential to satisfy the needs of the consumers and to fulfil their improved standard of living. Further, in the modern energy system, a significant function is played by the ELD. “The ELD can be defined as the process of allocating generation level to the generating units, so that the system load is supplied entirely and most economically. For an interconnected system, it is necessary to minimize the expenses”. The electric production need to be programmed correctly to reduce the operational cost. The major objective behind this research work is to generate the required amount of power with optimum cost. in worldwide. However, there exists increase in energy requirement as well as environmental issues like the emission from fossil fuel. In this research work, a non-conventional energy resource with RES is considered to overcome the problem of conventional method in electricity generation. However, with the introduction of the RES, the major challenges arise in terms of uncertainty and variability, which in turn leads to incur additional cost, termed as penalty cost. This can be minimized by selecting the optimal wind turbine.

Technical Constraints

Power Balance Constraints: To balance the power demand, the equality constraint should be satisfied. The overall generated power in thermal as well as wind power plant should be the same as total load demand added to the total line losses. Mathematically, it is represented as per Eq. (1). In addition, the transmission loss is mathematically expressed by the B- coefficient model as in Eq. (2).

$$\sum_{i=1}^{N_G} P_{Gi} + \sum_{k=1}^{N_W} P_{wk} = \sum_{j=1}^{N_D} P_{Dj} + P_{loss} \tag{1}$$

$$P_{loss} = \sum_{i=1}^{N_G}\sum_{k=1}^{N_G} P_{Gi}.B_{ik}.P_{Gk} \tag{2}$$

Where, $\sum_{i=1}^{NG} P_{Gi}$ is the total generation power of the system, P_{Gi} and P_{Gk} is the power output of i^{th} and k^{th} generator in MW and $\sum_{j=1}^{ND} P_{Dj}$ is the total demand power of the system. In addition, $\sum_{k=1}^{NW} P_{wk}$ is the total generated power by the wind power plants, P_{loss} is the power loss in the system.

Further, NG is the count of generating units, $ND$is the count of loads and NW is the count of wind generators in the network.

Active Power Generation Constraints: At each generators of the thermal power plant, the generated real power at i^{th} bus is restricted to be within the bounds of the maximal $P_{\max}^{Gi}$ and the minimal power limits $P_{\min}^{Gi}$. This is mathematically expressed in Eq. (3). The non-equality constraints of generated power by wind power plants are expressed in Eq. (3). Here, $w_{r,k}$ is the maximal generated power of the k^{th} wind turbine.

$$P_{\min}^{Gi} \le P_{\min} \le P_{\max}^{Gi} \;\; ; i = 1,2,..., N_G \tag{3}$$

$$0 \le w_k \le w_{r,k} \;\; ; k = 1,2,..., N_w \tag{4}$$

A. Problem Formulation

“ELD problem assumes that the amount of power to be supplied by a given set of units constants for a given interval of time and attempts to minimize the cost of supplying this energy subject to constraints of the generating units”. Therefore this research connects with the total cost minimization over the entire period of dispatch. The ELD is performed day-ahead for every 24 hours by scheduling all generators of the conventional bus system and wind turbines units in hourly time slots for the next day. Fig. 1 illustrates the scheme of ELD model. This is a dynamic, typical and multi-period decision problem. In this research work, the thermal power unit with IEEE 14 and IEEE 30 bus system is taken into consideration, therefore, the count of generators is 3 and 6, respectively. At each hour, the decision variables influence the decisions at the remaining hours. The scheme of the ELD model is shown in

Fig.1. The dispatch model get the input variables as wind turbine (in this research work 2 wind generation units are taken into consideration) and the load demand parameters over the planning period. The resulting power from all the controllable units is set as the decision variable or the control variable and it is set as P . The decision (control) variables are mathematically expressed as per Eq. (5).

$$P = P_1(1),\ldots.P_1(T)\ldots.P_i(t)..P_N(t)..P_N(T) \quad (5)$$

Here, N denotes the count of control variables and the overall count of time slot are denoted as T . In addition, $P_i(t)$ denotes the generated power from i^{th} unit at the t^{th} time slot.

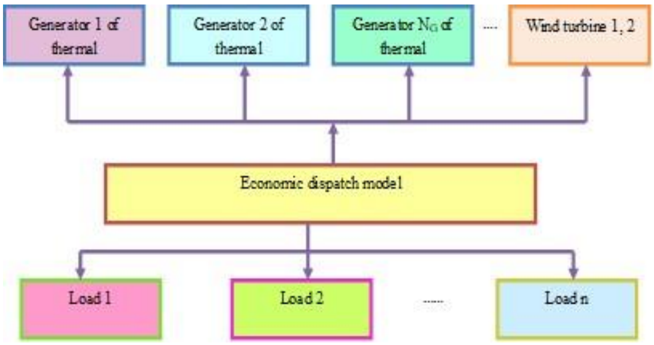


Figure 1. Scheme of ELD problem

TABLE I. FEATURES AND CHALLENGES OF EXISTING WORKS

Author [Citation]	Adopted Methodology	Features	Challenges
Sengar and Liu [1]	HMCS-DRNN approach	✓ Optimally meets the electrical requirement ✓ Multi-energy flow system offers improved outcome	◆ Produces maximum absolute error ◆ There is a requirement for optimal design and its stable operation of multi-energy system
Suresh *et al.* [2]	ADFA	✓ RES penetration level is improved ✓ Considers the power loss minimization objectives ✓ The voltage profile is enhanced ✓ The power loss is lessened	◆ The real power loss in the system need to be reduced significantly ◆ Require improvement in accuracy
Hamed *et al.* [3]	WNN and ANN	✓ Higher accuracy ✓ Smallest (MAPE and nRMSE) error ✓ Improve the variances for the data.	◆ Forecasting errors need to be reduced
Dey *et al.* [5]	WOA	✓ Provides better quality results ✓ Minimize the CEED problem	◆ Highly robust ◆ Need to handle complex constraints
Zhao *et al.* [6]	improved QPSO	✓ Microgrid EED problems can be solved ✓ Polluting gas emission is reduced	◆ Need to improve the accuracy of convergence ◆ The general costs of the model need to be reduced
Wang and Yang [7]	MAGSO algorithm	✓ Provides significantly robust solutions ✓ The quality of the optimal solution generated is higher	◆ Easily falls into the local optimal solution ◆ Convergence rate need to be increased
Tan *et al.* [8]	M-OODAA	✓ Total installed capacity is higher ✓ Higher utilization rate	◆ Renewable forecasting errors need to be reduced

IV. MULTI-OBJECTIVE FUNCTION FOR OPTIMAL ELD

In this section, the optimal ELD is explored for the power system including the wind power penetration. In this research work, two competing objectives i.e., "optimal power generation within limits and essential wind generation based on demand from wind turbine" are considered. In case of the ELD problem a multi-objective function inclusive of total wind generation cost, total cost function of thermal units and penalty cost function is considered.

A. Wind Power Generation

The major challenge that occurs in the power system during the integration of the wind output power is its uncertainty, fluctuation, and intermittent nature. Therefore, the wind power output needs to be a stochastic variable from wind speed to power output. The relationship between the generated power and the random nature of wind speed is expressed in Eq. (6).

$$w = \begin{cases} 0 & for \quad V < V_k \; and \; V > V_o \\ w_r \dfrac{(V - V_k)}{(V_r - V_k)} & for \quad V_k \le V \le V_r \\ w_r & for \quad V_r \le V \le V_o \end{cases} \quad (6)$$

Where, V is the current wind speed in (m/s), V_k is the cut-in wind speed, V_o is the cut-out wind speed and V_r is the rated wind speed. In addition, the turbine's output power is symbolized as $wind$ and the rated power of the turbine is described as w_r.In the current research work, two wind power systems are considered to meet the demands in the power. From the above Eq. (5), a conclusion can be obtained as:

- ✓ "The generated power of wind turbines is set to zero, if the velocity of the wind crosses over the turbine's speed limits.
- ✓ Within the rated range of the wind speed and the cut-in wind speed, a linear formulation can be defined between output power and wind speed.
- ✓ The output power from the wind turbine is equivalent to the rated power output between rated wind speed and cut-out wind speed".

The total power generated by the wind turbine is expressed as per Eq. (7).

$$E^{wind} = \sum_{w=1}^{N_w} \frac{P_0 A v_{wind}^3 L^p}{2 G_k T} e^{-\frac{gJ}{G_k T}} \quad (7)$$

Here, E^{wind} *is the total energy generated by the wind turbines. The atmospheric pressure* P_0 *of seat level (101325 Pa). The swept area is defined as* A *and turbine's power* coefficient is specified as L^p. In addition, the definite gas constant of air (287 J/(kg.K)) is denoted as G_k, and the gravitational constant and wind turbine's veloclty is symbolized as g and v_w, respectievly. Further, J is the altitude in meters and the temperature is specified as T (in kelvin), which is defined as $T = T_0 - FJ$, where T_0 indicates the temperature of sea level (288K) and F denots the rate of temperature lapse (0.0065 $^\circ C/m$).

B. Objective Function

The major objective of ELD including wind power is to minimize the wind cost, penalty cost and total fuel cost of thermal generators by satisfying all the constraints. Then, the multi-objective function can be represented as a single objective as shown in Eq. (8). Here, TC_{total} is the total cost in \$/h.

$$Ob = \min(TC_{total}) \quad (8)$$

$$TC_{total} = TC_{Generation} + TC_{wind} + TC_{penalty} \quad (9)$$

Here, TC_{wind} is the total wind generation cost, $TC_{Generation}$ is the total cost function of thermal units and $TC_{penalty}$ is the penalty cost function.

(a) Cost function of thermal units $TC_{Generation}$: it is mathematically shown in Eq. (10). Here, a_i, b_i and c_i are the i^{th} coefficients of the thermal unit. The generated output power is denoted as P_{Gi} and $C_{thermal,i}$ is the fuel cost of the thermal unit.

$$TC_{Generation} = \sum_{i=1}^{N_G} C_{thermal,i}(P_{Gi}) = \sum_{i=1}^{N_G} (a_i P_{Gi}^2 + b_i P_{Gi}^2 + c_i) \quad (10)$$

(b) Cost function of wind unit TC_{wind}: The wind generation cost is shown in Eq. (11). Here, d_k is j^{th} wind generator's direct cost coefficient.

$$TC_{wind}(w_k) = d_k . w_k \quad (11)$$

(c) Penalty cost $TC_{penalty}$: Three conditions are set for incurring the penalty cost

- If $P_{Dj} > P_{Gi} + P_{wk}$, then penalty =2
- If $P_{Dj} = P_{Gi} + P_{wk}$, then penalty =0
- If $P_{Dj} < P_{Gi} + P_{wk}$, then penalty cost=1

On the basis of this objective, the produced power is optimally created within the bounds of the maximal $P_{\max}^{Gi}$ and the minimal power limits $P_{\min}^{Gi}$ using the optimization concept. In addition, based on the power demand, the turbines will be operated optimally by the optimization algorithm. In this research work, 2 wind turbines are utilized and they are selected by the optimization algorithms based on the length of the chromosomes as shown in Table II.

TABLE II. OPTIMAL TURBINE SELECTION

Chromosome length	**Turbine selection**
01	Select 2nd turbine
10	Select 1st turbine
11	Select both turbines
00	Select no turbines

In this research work, an analytic evaluation is done with various optimization algorithms like DA [26], FF [27], GWO [28], SLnO[29] and MFO [30]. The solution fed as input to them is shown in Fig.2. Here, the best optimization algorithm will be explored that is good in generating the optimal power within the bounds limits and optimally selecting the turbines based on demand.

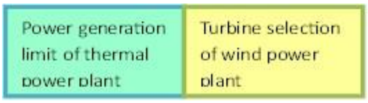


Figure 2. Solution Encoding

The optimal power generation bounds for IEEE-14 and IEEE-30 bus system is shown in Table III and Table IV, respectively.

TABLE III. OPTIMAL POWER GENERATION BOUNDS FOR IEEE-14 BUS SYSTEM

Generators(Gen)	P^{min}	P^{max}
1	10	160
2	20	80
3	20	50

TABLE IV. OPTIMAL POWER GENERATION BOUNDS FOR IEEE-30 BUS SYSTEM

Generators(Gen)	P^{min}	P^{max}
1	50	200
2	20	80
3	15	50
4	10	35
5	10	30
6	12	40

The power generated by each of the generators(Gen) of IEEE-14 bus system for diverse optimization algorithm is tabulated in Table V. The power generated by each of the generators of IEEE-30 bus system is shown in Table VI and Table VII respectively.

FF [27]: The algorithm was developed on the basis of the inspiration of fireflies. The procedure standardizes is as given below.

- Fireflies get attracted to others, irrespective of sex.
- The attarctivess of the fireflies is directly proportioal to its brightness. Fireflies with lesser brightness are attracted to those with better brightness. Fireflies travel randomly if they are not capable to find out brighter fireflies
- Technically, the brightness of fireflies is based on objective functions.

GWO [28]: In general, GWO is a renowned algorithm that is based on both leadership as well as hunting behavior of grey wolves. The levels of this model are: alpha is the initial level that acts as the troop leaders (male and female). They also take decisions in terms of sleeping place, hunting, walking time, and etc. Beta is the next level that aids in taking decisions. Delta is the third level that named as subordinates. Final level is omega that concerned as the scapegoat. In this, , and guides in the procedure of hunting.

DA [26]: The motivation of DA [130] initiates from static as well as dynamic behaviors of swarm. Two behaviors must be followed: Attraction and distraction. Attraction must be towards the food source and distraction must be from enemies. Five factors are there in this algorithm: "(1) Control cohesion (2) Alignment (3) Separation (4) Attraction (5) Distraction". MFO [30]: The moths are the fancy insects that are embedded with a special navigation mechanism for night movement along the moon light. A fixed angle is maintained by the moths in correspondence to the moon for traveling in straight path over longer distance. The transverse orientation mechanism guarantees the straight-line movement of moth since the moon is far away from it. SLnO [29]: It was developed on the inspiration from the sea lions' hunting behaviour. The whiskers of the sea lions help in detecting the prey. In nature, the sea lions are gifted with certain fascinating characters like clear vision, faster movement and better hunting property. The stages of the SLnO are: prey tracking and chasing, prey encircling and attacking.

TABLE V. OPTIMAL POWER GENERATED FOR EACH HOUR BY DIVERSE OPTIMIZATION ALGORITHM IEEE-14 BUS SYSTEM

Hour	**DA**			**FF**			**GWO**			**SLnO**			**MFO**		
	Gen-1	**Gen-2**	**Gen-3**	**Gen-1**	**Gen-2**	**Gen-3**	**Gen-1**	**Gen-2**	**Gen-3**	**Gen-1**	**Gen-2**	**Gen-3**	**Gen-1**	**Gen-2**	**Gen-3**
1	58.619	64.73	50	43.577	19.623	30.039	12.119	20.26	20.482	72.402	55.765	24.339	160	80	35.858
2	57.036	41.623	31.933	81	31.709	24.751	15.206	20.027	20.259	54.674	56.803	29.404	159.2	80	50
3	88.06	59.494	27.595	82.024	52.045	41.611	16.895	21.156	20.515	80.255	62.308	37.871	160	78.78	26.59
4	19.267	60.922	31.255	60.368	21.269	56.492	15.136	21.391	25.894	58.339	34.954	30.138	10	80	49.157
5	10	59.687	32.084	32.902	57.933	22.551	12.592	20.085	20.052	46.622	26.13	27.078	151.2	58.227	21.223
6	80.466	80	38.065	66.943	21.095	22.987	14.031	21.297	20.563	62.698	37.695	34.349	160	44.536	26.977
7	82.221	66.205	21.53	37.413	44.634	34.681	16.127	20.043	20.693	32.149	25.936	39.597	10	20.317	20

8	131.69	62.086	50	39.37	54.25	33.916	12.559	21.176	20.645	68.629	41.855	33.4	102.46	22.131	20
9	46.57	22.128	35.023	55.8	54.783	28.864	10	21.281	23.188	29.874	47.019	34.127	10	61.878	20
10	71.474	20	50	83.614	42.675	28.573	18.151	20.13	22.227	71.163	51.441	27.079	88.413	80	20
11	113.43	80	48.318	53.515	12.978	85.152	14.736	20.682	20.001	29.478	37.487	28.307	10	20	33.676
12	49.688	39.808	31.698	77.055	19.407	45.623	10.517	21.625	22.468	54.988	37.093	30.777	160	20	50
13	30.286	37.164	43.047	28.083	34.844	49.377	15.95	21.112	20.42	37.972	62.922	25.651	155.94	20	45.629
14	79.594	51.738	37.767	90.825	60.462	28.78	14.33	20.446	20.28	90.588	57.802	34.616	13.06	23.184	49.802
15	58.58	20	42.528	131.59	35.851	116.15	10.383	20.131	23.525	94.475	67.918	23.968	83.268	80	20.392
16	108.14	64.468	25.176	125.02	82.278	51.037	10.773	20.241	20.29	50.834	47.539	29.149	158.57	20.199	50
17	108.77	39.11	50	49.298	16.475	41.141	10.978	20.84	20.029	71.563	42.037	24.912	17.615	20	50
18	73.044	54.116	47.085	25.15	65.122	21.1	11.566	21.295	20.63	89.307	52.312	41.624	16.299	77.765	20.968
19	71.504	21.833	23.984	27.129	12.267	18.643	10.174	25.171	22.124	86.103	24.35	24.356	25.421	72.512	23.152
20	41.161	41.702	20	35.813	31.347	35.201	11.11	20.454	22.876	75.318	31.018	29.646	47.259	72.139	36.957
21	46.178	55.974	36.157	41.944	45.461	43.423	11.664	20.462	20.43	97.185	40.748	34.251	139.65	22.469	50
22	10.355	26.285	50	10.325	29.672	43.508	18.171	20.374	20	89.843	32.723	27.178	10	20	49.919
23	86.052	38.419	26.353	13.469	45.46	33.835	11.725	20.749	20.112	47.38	44.735	39.265	147.5	39.607	46.023
24	160	31.445	39.071	15.684	24.623	21.961	11.026	20.31	21.026	51.279	36.227	30.035	10	52.417	49.954

TABLE VI. OPTIMAL POWER GENERATED FOR EACH HOUR BY DIVERSE OPTIMIZATION ALGORITHM (DA, FF, GWO) IEEE-30 BUS SYSTEM

	DA						FF						GWO					
Hour	Gen-1	Gen-2	Gen-3	Gen-4	Gen-5	Gen-6	Gen-1	Gen-2	Gen-3	Gen-4	Gen-5	Gen-6	Gen-1	Gen-2	Gen-3	Gen-4	Gen-5	Gen-6
1	73.889	60.363	15	21.949	17.022	30.488	80.668	72.687	15.959	26.762	18.346	27.643	62.235	30.097	23.921	11.874	17.192	18.045
2	66.741	32.29	37.519	35	12.724	28.663	71.058	31.886	43.026	34.207	16.268	31.385	56.27	24.502	22.727	11.547	10.693	13.666
3	137.3	56.995	26.376	10.942	11.552	27.216	181.46	73.676	17.977	10.976	13.397	36.588	50.219	20.181	25.288	16.553	10.747	30.969
4	52.721	43.609	50	24.71	20.643	19.325	64.752	45.266	48.526	23.329	23.838	20.834	52.034	38.528	15.433	19.557	10.324	15.276
5	129.03	56.112	15	25.535	30	24.162	152.98	70.078	15.64	28.754	29.777	32.949	51.402	20.129	15.892	10.164	10.638	13.346
6	76.029	69.906	19.183	20.04	27.741	15.466	92.067	67.357	18.613	21.197	28.172	20.221	55.004	21.892	16.854	17.903	12.743	14.067
7	87.601	26.497	15	19.6	11.298	20.522	93.166	27.802	15.678	26.971	14.233	19.435	53.724	20.538	27.08	28.738	12.076	20.605
8	96.528	20	32.712	10	17.415	23.432	123.74	23.202	35.094	13.668	21.786	31.593	71.46	28.915	22.446	14.725	14.839	12.53
9	69.216	36.693	30.065	18.469	11.457	23.899	65.35	44.843	39.304	20.354	10.999	27.005	53.779	56.092	20.773	12.411	15.78	12.003
10	118.76	37.189	46.716	25.774	24.95	14.465	149.57	50.893	48.061	24.664	28.068	15.849	55.887	46.321	17.004	19.963	14.833	12.156
11	78.143	64.538	28.683	16.966	25.443	22.584	70.891	68.443	28.919	14.134	28.55	21.737	58.253	28.542	16.834	19.974	12.56	21.813
12	142.65	64.723	42.53	29.281	24.461	17.898	162.62	63.56	45.916	25.592	25.019	21.769	75.444	21.945	16.035	14.948	11.708	14.672
13	58.484	57.018	28.727	35	24.764	28.664	90.489	73.753	29.983	34.121	23.269	29.407	50.016	24.966	20.214	16.309	10.671	20.245
14	99.414	80	21.129	20.667	12.349	14.162	67.212	76.969	30.747	24.46	18.163	18.637	85.603	32.175	18.537	10.606	20.122	15.906
15	173	40.597	15	28.678	15.599	19.716	185.51	54.421	15.1	25.429	16.533	26.758	51.811	21.445	16.89	10.037	16.162	13.366
16	137.16	26.239	39.98	29.237	10	40	182.89	41.436	46.799	25.584	10.316	38.024	57.132	44.082	15	13.137	10.688	17.969
17	178.33	80	15	12.517	26.794	28.89	153.63	79.839	21.032	13.428	28.652	31.511	51.592	21.204	25.347	28.593	12.044	20.103
18	50	67.928	41.84	25.065	21.5	14.389	59.9	65.328	41.386	33.076	24.23	15.48	50.181	30.7	16.378	17.022	15.31	17.307
19	50	20	15	14.069	24.31	26.651	52.982	21.573	15.991	16.155	27.201	27.087	67.52	22.441	15.837	11.005	21.49	17.288
20	128.64	60.96	17.611	12.384	14.801	40	132.92	70.522	19.346	16.98	21.715	39.149	51.096	20.178	15.614	10.82	14.926	17.983
21	116.8	20	37.865	13.604	23.965	13.004	134.15	21.119	43.022	15.824	26.142	22.86	50	21.195	19.581	15.507	17.358	14.871
22	140.99	51.804	31.605	10	11.315	13.621	179.53	64.827	34.468	13.411	11.198	15.398	52.034	22.305	18.849	11.266	11.547	17.137
23	58.379	25.506	16.795	19.234	21.461	12	56.683	26.45	22.9	27.825	21.194	12.352	54.916	21.832	22.259	14.425	10.843	27.509
24	50	80	27.396	11.519	10	27.538	60.796	78.037	34.884	15.082	15.047	32.827	59.443	23.827	21.666	32.499	11.314	18.367

TABLE VII. OPTIMAL POWER POWER GENERATED FOR EACH HOUR BY DIVERSE OPTIMIZATION ALGORITHM (SLnO AND MFO) IEEE-30 BUS SYSTEM

	SLnO						**MFO**					
Hour	**Gen-1**	**Gen-2**	**Gen-3**	**Gen-4**	**Gen-5**	**Gen-6**	**Gen-1**	**Gen-2**	**Gen-3**	**Gen-4**	**Gen-5**	**Gen-6**
1	86.012	46.485	28.745	18.567	11.839	15.658	80.668	72.687	15.959	26.762	18.346	27.643
2	83.083	34.457	22.969	15.406	17.24	20.483	71.058	31.886	43.026	34.207	16.268	31.385
3	135.79	45.363	22.038	13.584	10.278	24.752	181.46	73.676	17.977	10.976	13.397	36.588
4	54.969	45.537	25.982	14.98	15.364	15.358	64.752	45.266	48.526	23.329	23.838	20.834
5	73.281	30.588	29.554	15.774	10.339	24.891	152.98	70.078	15.64	28.754	29.777	32.949
6	102.97	66.944	42.462	23.244	15.491	18.109	92.067	67.357	18.613	21.197	28.172	20.221
7	84.004	28.561	18.132	11.409	12.371	23.068	93.166	27.802	15.678	26.971	14.233	19.435
8	107.6	39.378	24.224	13.333	19.98	22.882	123.74	23.202	35.094	13.668	21.786	31.593
9	52.44	48.869	22.519	11.93	17.98	20.899	65.35	44.843	39.304	20.354	10.999	27.005
10	73.454	23.071	19.652	14.649	12.959	21.411	149.57	50.893	48.061	24.664	28.068	15.849
11	54.941	39.017	16.043	15.487	20.174	28.407	70.891	68.443	28.919	14.134	28.55	21.737
12	57.153	46.965	22.883	23.278	23.914	25.339	162.62	63.56	45.916	25.592	25.019	21.769
13	132.66	33.401	25.008	11.326	11.306	31.511	90.489	73.753	29.983	34.121	23.269	29.407
14	94.074	23.981	16.141	14.213	20.18	14.941	67.212	76.969	30.747	24.46	18.163	18.637
15	62.378	61.139	38.135	17.46	13.935	27.777	185.51	54.421	15.1	25.429	16.533	26.758

16	74.359	41.227	21.148	24.57	18.593	14.063	182.89	41.436	46.799	25.584	10.316	38.024
17	89.208	32.087	16.547	15.999	14.716	20.763	153.63	79.839	21.032	13.428	28.652	31.511
18	81.703	49.859	31.528	23.915	12.938	13.44	59.9	65.328	41.386	33.076	24.23	15.48
19	124.74	24.58	17.76	27.936	18.202	16.966	52.982	21.573	15.991	16.155	27.201	27.087
20	93.065	21.526	27.956	11.919	10.05	22.421	132.92	70.522	19.346	16.98	21.715	39.149
21	139.79	27.25	26.626	11.514	13.397	29.928	134.15	21.119	43.022	15.824	26.142	22.86
22	144.45	29.7	31.914	13.005	18.294	19.392	179.53	64.827	34.468	13.411	11.198	15.398
23	191.04	36.974	28.23	14.616	14.98	12.083	56.683	26.45	22.9	27.825	21.194	12.352
24	79.375	33.17	22.221	19.189	10.574	14.611	60.796	78.037	34.884	15.082	15.047	32.827

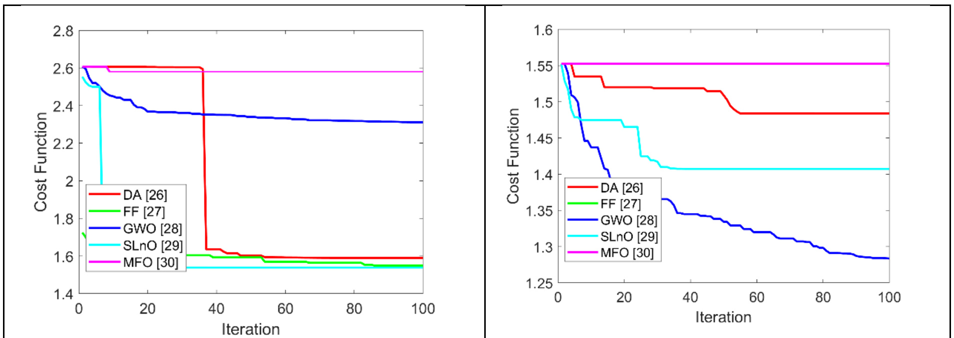
V. RESULTS AND DISCUSSION

A. *Simulation procedure*

The analytical evaluation on optimization algorithms for exploring solution to ELD problem was done in MATLAB and the resultant acquired was noted. This evaluation was done using various optimization algorithms like DA [26], FF [27], GWO [28], SLnO[29] and MFO[30]. Further, the assessment of the model is made in terms of convergence and demand power. The datasheet for IEEE-14 bus system is collected from [37] and the data for IEEE-30 bus system is collected from [36].

B. *Convergence Analysis*

The convergence analysis is a fundamental factor that portrays about the attainment of the objective function. In this research work, the objective function is the minimization of the total cost that includes the cost of the thermal power function, cost of wind power function and penalty cost function. Among the approaches taken into consideration, the algorithm with lower convergence is said to be the best one. The graphical resultant of convergence corresponding to IEEE-14 and IEEE-30 bus function is shown in Fig.3, respectively. Here, the evaluation is done by varying the count of iterations. The X-axis of the graph describes the iterations and Y-axis tells about the attained cost function. In Fig. 3(a) and Fig. 3(b), the convergence of IEEE-14 bus system is higher for all the methods at lower count of iterations. As the count of iterations tends to increase, the cost function slowly and gradually decreased and attained the minimal limits. In case of IEEE-14 bus system, the lowest cost function at 100th iteration is recorded by MFO and its value lies between 1.46 and 1.6. The cost function of MFO is 6.25%, 6%, 11.7%, 36% and 46.42% better than the cost function of FF, SLnO, DA, GWO and MFO, respectively. In addition, the cost function of IEEE-30 bus system from Fig. 3(b) also shows the lowest convergence with highest iterations. Here, at 100th iteration, the lowest convergence is recorded by GWO and its cost function resides between 1.25 and 1.3. The cost function of MFO is 10.7%, 16.6%, 13.3% and 13% better than the existing models like SLnO, DA, MFO and FF, respectively.

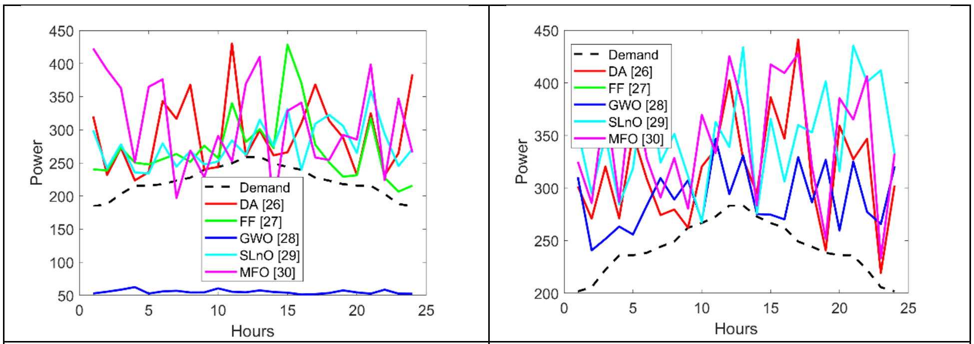


(a) (b)

Figure 3. Convergence analysis of diverse optimization algorithm for (a) IEEE-14 bus system and IEEE-30 bus system

C. *Evaluation on Demand Response*

The demand response of the diverse optimization algorithms for IEEE-14 and IEEE-30 bus system is shown in Fig.4. In general, Demand response termed to be the power consumption change of customer's electric utility to better match the power demand with the supply. Here, the evaluation is done by varying the time period (hours) in X-axis and its corresponding power demand is shown in Y-axis. In Fig. 4(a) corresponding to IEEE-14 bus system, the power is above 200kwatts below 300kwattas for the time period of 24 hours. The optimal power generated by GWO is much lower than the demand and hence it is insufficient to meet the power demand, the all other methods can somehow meet the demands of the power. In certain periods, the power generated is greater than the limits and hence the losses are more. In addition, for IEEE-30 bus system, the power demand is between 150kwatts to 275kwatts. The GWO can generate the power much lower than the demand and hence not suggested for optimal power generation.



(a) (b)

Figure 4. Power demand analysis of diverse optimization algorithm for (a) IEEE-14 bus system and IEEE-30 bus system

VI. Conclusion

In this work, an analytical evaluation is undergone with diverse standard optimization algorithms on providing solution to ELD problem under multi-objectives. The multi-objectives like total wind generation cost, total cost function of thermal units and the penalty cost function were taken into consideration. In addition, the power generation is made optimal within the maximum and the minimum bounds using the optimization algorithm. In addition, to make the power generation of wind turbine meet the power demands, the turbines were selected optimally using the optimization algorithm. Finally, an algorithmic evaluation was done with IEEE-14 and IEEE-30 bus system in terms of convergence and demand response.

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