Integrated Economic and Emission Dispatch of Hybrid Thermal-Photovoltaic Generation

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ABSTRACT

Due to the increasing demand for qualitative electric energy at a competitive price and reduced environmental deterioration, electric power generation systems should be optimally dispatched. In this paper, the Integrated Economic and Emission Dispatch (IEED) of hybrid thermal-photovoltaic power plants using Bat (Chiroptera) Inspired Algorithm (BIA) is presented. The IEED technique entails determining the optimal scheduling of the electricity generating units, to meet the system load, at the lowest possible cost and reduced greenhouse gases emission, subject to network constraints. While thermal power plants are dispatchable, a photovoltaic (PV) system is non-dispatchable. Hence, the solution of the proposed IEED comprises of the optimal real power generation of the thermal units and binary (ON-OFF) states of the PV system. The nonlinearity in the fuel cost function of the generators, valve-point loading effect of the thermal units, and need for faster convergence inform the choice of BIA for the proposed IEED. The proposed method is implemented in MATLAB software, and simulation is performed using IEEE 57-bus systems, with 30 hybrid thermal-PV generating units test system. From the simulation carried out, the proposed method has calculated the optimal solutions, reduced 31.23% and 27.09% of the fuel and emission costs respectively, without violating any system constraints.

1. INTRODUCTION

Conventional power plants like hydroelectric, nuclear or other thermal power plants are not located close to the load centers and their fuel costs differ (Wood & Wollenberg, 2014; Malyscheff et al., 2019). It is therefore essential to determine the real (active) and reactive power scheduling of each power plant (which vary within some certain limits) so as to reduce the operating costs (A.Eladl & ElDesouky, 2019; Nghitevelekwa & Bansal, 2018) and environmental emission (Yalcinoz, 2002) known as Economic Dispatch (ED) and Environmental Emission Dispatch (EED) respectively. These generation schedules must not violate unit maximum and minimum operating limits, prohibited operating zones, ramp rates and must equally meet the power demands.

Majority of the standalone photovoltaic (PV) systems previously installed in developing countries are off-grid for power supply applications to remote locations. Even the few grid-connected PV systems in developed countries are at low voltage distribution level injecting few kilowatts into the grid. This is why, numerous researches on ED and EED seldom consider incorporating PV systems as part of the generating units to be optimized. The challenges associated with integration of huge photovoltaic systems to transmission and sub-transmission networks, such as intermittency, also attribute to the neglect of PV system in the ED researches (Nghitevelekwa & Bansal, 2018). However, with the recent increased penetration of these systems at various voltage levels (reaching roughly 637 GW in 2018), the need to carryout Integrated Economic and Emission Dispatch (IEED) with hybrid thermal-photovoltaic system became eminent.

Renewable Energy Sources (RES) such as PV and wind power systems are inherently non-dispatchable and intermittent. In order to make them dispatchable and overcome the intermittency problem, energy storage systems such battery systems and ultra-capacitors are incorporated to make the generated power steady. Through controlled charging and discharging of the energy storage devices, these intermittent RES can be dispatched on hourly, half- and quarter-hourly basis just like any other conventional generating unit (Nghitevelekwa & Bansal, 2018).

IEED is a multi-objective optimization problem of hybrid thermal–photovoltaic generating plants that allocates power to each online generating unit in order to decrease the total cost of operation and greenhouse gases emission to their respective minima devoid of violating the constraints. This is necessary in order to quantity emission in economic terms with a view to generating an inclusively consistent objective function, especially since these quantities have different units. Lambda iteration (LI) and Lagrangian relaxation are the oldest techniques applied to solve ED problem (Chenb, 2003; Premrudeepreechacham, 2007). Recently, several techniques have been introduced and put in place for the solution of ED and EED, among which are Particle Swarm Optimization (PSO) (Yuewen & Wen, 2007; Behnam et al., 2013), Linear Programming (LP), Immune Algorithm (IA) (Arag et al., 2015), Differential Evolution (DE), Artificial Neural Network (ANN) (Premrudeepreechacham, 2007), Euclidean Affine Flower Pollination Algorithm (EFPA) (Shilaja & Ravi, 2017), oppositional invasive weed optimization (Barisal & Prusty, 2015), fuzzy logic (Liang R. H., 2007; Liang & Liao, 2007), Firefly Algorithm (FFA) (Gupta & Padhy, 2016), Genetic Algorithm (GA), Non-dominated sorting hybrid Cuckoo Search Algorithm, Hybrid Harmony-Gravitational Search Algorithm, Artificial Bee Colony (ABC) optimization. LI and LP approaches have been implemented widely for ED applications due to the fact that the former is easy to implement while the latter can handle operational constraints. However, the LI can only deal with static ED and LP approach usually faces poor computation efficiency (Dustin et al., 2019).

Although the aforementioned heuristic and meta-heuristic optimization techniques have presented remarkable performance while solving ED problems, they suffer from one or more drawbacks. For instance, GA requires a large computational time. In addition, IA and DE often converge prematurely while ABC lacks good exploitation ability. Among other drawbacks faced by some of these techniques, especially with complex and non-convex objective functions include trapping in local optimal solutions and need for tuning several parameters (Xia & Elaiw, 2010). To tackle some of the aforementioned limitations, (A.Eladl & ElDesouky, 2019) proposed a bi-level hybrid PSO technique and Sequential Quadratic Programming (SQP) method for ED of multi-source power systems. To address some of the limitations, advanced and robust techniques for solving the non-convex problems are required. As a result, there are ongoing research works aimed at developing more robust meta-heuristic techniques with the ability of finding the global optimal solution irrespective of the nature of the objective functions or constraints. Among the new promising meta-heuristic techniques are Bat Inspired Algorithm (BIA) (Xin-She, 2010), FFA (Gupta & Padhy, 2016) and non-dominated sorting hybrid Cuckoo Search Algorithm (Nghitevelekwa & Bansal, 2018)

Thus, in this paper, an IEED of hybrid thermal-photovoltaic power plants using Artificial Bat Inspired Algorithm (ABIA) is proposed. The technique is chosen due to its faster convergence at a very early stage by swapping between exploration and exploitation. The presented IEED is a multi-objective optimization problem. However, it is transformed to a single one with the aid of a penalty factor in the objective function. The unique contributions of this paper are itemized below: -

i. Application of BIA to solve IEED problem considering valve-point loading effect.
ii. The IEED is carried out subject to generation-demand balance, generation limits and thermal units’ ramp rate constraints.
iii. Reduction of 31.23% and 27.09% in the fuel and emission costs are respectively obtained.

The outline of this paper is organized as follows. After this introductory section, mathematical formulation of the IEED is presented in Section II. In Section III, concept of ABIA is reviewed while Section IV describes the test system used for the simulation. Simulation results and discussion are presented in Section V. The paper is concluded with Section VI.

2. OPTIMAL ECONOMIC DISPATCH FORMULATION

In this section, mathematical formulation of the proposed multi-objective IEED problem is presented.

2.1 Objective Function

The aim of the IEED is to minimize the fuel cost and environmental emissions by determining the optimal power output of a hybrid thermal-PV generating units while satisfying the constraints. It is formulated as follows:

$$\min_{P_{Gi}} C_T$$

Where, $C_T = \sum_{i=1}^{n}\{F(P_{G_i}) + E(P_{G_i})\} + \sum_{j=1}^{v} \psi_j C_{pv_j}$ (1)

The terms *F* and *E* are non-linear cost functions of generated power, $F(P_{G_i})$ and $E(P_{G_i})$ represent fuel cost and emission cost of i^{th} generating unit. ψ_j represents binary (0, 1) states of the PV system indicating the optimal state of 1 (online) or 0 (offline). Similarly, n and v are numbers of thermal and PV units, respectively. Other notations used in the IEED formulation are presented in the nomenclature. As presented in (1), the objective function has two key components; fuel and emission costs associated with thermal power plant and that associated with solar power plant installation.

2.2 Thermal Power Plant

Usually, the fuel cost of thermal generators, $F(P_{Gi})$ is modelled as a quadratic function of active power generation as given in (2) (Kishore *et al.*, 2018; Saadat, 1999):

$$F(P_{G_i}) = (a_i + b_i P_{G_i} + c_i P_{G_i}^2) \quad (2)$$

However, considering the Valve-Point Loading Effect (VPLE), the fuel cost is modified to a nonlinear and non-smooth form as given in (3):

$$F(P_{G_i}) = (a_i + b_i P_{G_i} + c_i P_{G_i}^2) + |d_i sin[e_i(P_{Gi}^{min} - P_{G_i})]| \quad (3)$$

The absolute value term in (3) which is modeling the VPLE, makes the function non-differentiable. Non-differentiability encountered is resolved by using a hyperbolic smoothing proposed in (Chen, 2012). In the same vein, the environment emission cost, $E(P_{Gi})$ is defined as follows:

$$E(P_{G_i}) = (\alpha_i + \beta_i P_{G_i} + \gamma_i P_{G_i}^2) + \tau_i e^{\xi_i P_{G_i}}$$

2.3 Photovoltaic System

Photovoltaic sources use cells that depend on the "photovoltaic" effect to convert incident sunlight into DC electric power. The DC power is then transformed to AC electric power at the system frequency using a power inverter. Small arrays of photovoltaic cells can be placed on the roof of a single home and supply electric power to that home or large number of arrays can be arranged in fields and wired to supply power directly to the electric power system (Kishore *et al.*, 2018). As such, PV systems could either be grid connected or stand-alone. There are variety of PV technologies available with different efficiencies, so the PV power generation is not only affected by weather condition variations but also the module specifications.

Photovoltaic power generation is green power and therefore makes a great contribution to reduce carbon emission for power industry. The power generated from solar plants is computed using (5):

$$P_{PV} = \frac{G \times P_{rated}}{G_{ref}}\left\{1 + \eta\left(T_{amb} - T_{ref}\right)\right\} \quad (5)$$

Where T_{ref} and T_{amb} represent reference and ambient temperatures, while G and G_{ref} stand for the incident and reference solar radiation respectively. P_{rated} is the rated power of a PV unit or plant and η (expressed in %/°C) is the temperature coefficients (also regarded as maximum power temperature coefficient), and is a negative number that shows how the PV array power output hinges on the cell temperature (Homer, 2019).

It can be seen that solar irradiance and ambient temperature are the key factors influencing the output power of solar plant. The total installation cost of j[th] plant share is represented as:

$$C_{pv} = \sum_{j=1}^{v} C_{pv_j}^{pu} \times P_{pv_j}^{avail} \quad (6)$$

2.4 Constants

The proposed IEED is a non-linear optimization problem carried out subject to some system and operational equality and inequality constraints formulated as follows:

- *Generation-demand balance*: total generated power must, meet up with the total demand (with losses inclusive) as given in (7):

$$P_D + P_L = \sum_{i=1}^{n} P_{G_i} + \sum_{j=1}^{v} \psi_j P_{pv_j} \quad (7)$$

Where the total power loss, P_L is calculated based on *T*-coefficient matrix as follows (Saadat, 1999):

$$P_L = T_{oo} + \sum_{i=1}^{k} T_{oi} P_{Gi} + \sum_{i=1}^{k}\sum_{j=1}^{k} P_{Gi} T_{ij} P_{pvj} \quad \forall\, i, j = 1, 2, \dots, k \quad (8)$$

Where T_{oo} (MW), T_{oi} and T_{ij} (MW^{-1}) are the *T*-coefficients (Kumar & Dhillon, 2018).

- *Generation limits*: the generators are constrained to generate power within certain minimum and maximum limits as given in (9):

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max} \quad \forall\, i = 1, 2, .., n \quad (9)$$

While determining the optimal solution, a particular solution or a set of solution may appear to violate the above–mentioned constraints. Though there are numerous techniques that are efficient in handling constraints, such as methods that preserve the feasibility of solution and penalty-based methods (commonly applied for solving IEED problem by AI techniques (Xia & Elaiw, 2010)), in this proposed work, the solution is constrained as illustrated in (10) (Kishore *et al., 2018*):

$$P_{G_i} = \begin{cases} P_{Gi}^{min}, & if\ P_{G_i} \le P_{Gi}^{min} \\ P_{Gi}^{max}, & if\ P_{G_i} \ge P_{Gi}^{max} \\ P_{G_i}, & Otherwise \end{cases} \quad (10)$$

- *Thermal Power Units Ramp Rate Constraints:* The rate of change of power generation of each thermal unit, *i* is constrained within certain finite ramp-up rate, U_i^{rate} and ramp-down rate, D_i^{rate} limits as given in (11) and (12):

$$P_{Gi}(t) - P_{Gi}(t-1) \le U_i^{rate} \quad (11)$$

$$P_{Gi}(t-1) - P_{Gi}(t) \le D_i^{rate} \quad (12)$$

In (1), the term minimizing the fuel cost can dominate the aggregated cost, C_T. To avoid this, the multi-objective optimization formulated in (1) is transformed to a single objective through the introduction of a unit less weighing or penalty factor, μ_i for each unit *i* as given in (13):

$$C_T = \sum_{i=1}^{n}\{F(P_{Gi}) + \mu_i E(P_{Gi})\} + \sum_{j=1}^{v} \psi_j C_{pv_j} \quad (13)$$

The penalty factor is computed using (14):

$$\mu_i = \frac{\left(a_i + b_i P_{Gi} + c_i {P_{Gi}}^2\right) + \left|d_i sin\left[e_i\left(P_{Gi}^{min} - P_{Gi}\right)\right]\right|}{\left(\alpha_i + \beta_i P_{Gi} + \gamma_i {P_{Gi}}^2\right) + \tau_i e^{\xi_i P_{Gi}}} \quad (14)$$

3 ARTIFICIAL BAT INSPIRED ALGORITHM TECHNIQUE

Bat (Chiroptera) Inspired Algorithm (BIA) technique, pioneered by Yang (Xin-She, 2010), is a search algorithm developed based on the echolocation behavior of bats in locating their victims. To adapt to their environs, bats emit a sequence of ultrasound pulsations and listen for the echoes that reflect back from the neighboring objects (Yang & He, 2013). The nature of waves emitted by a bat of a particular specie differ from the waves of another specie. The waves bounce with time delays and altered sound levels thereby making the bats to sense and catch a particular prey (Elsisi et al., 2016). The summary of the procedures involved in BIA are itemized below:

Step 1: All the artificial bats apply echolocation to detect the proximity amid prey and barrier;

Step 2: Each artificial bat flies at certain velocity (v_i) at position (x_i), with constant frequency (f_i), changing wavelength (λ), and loudness (L_o) to pursue a prey. The bat adjusts the f_i of its emitted pulse within the interval [f_{min}, f_{max}] and adjusts the rate of pulse emission (r) within the interval of [0, 1] based on the target's proximity as shown in (15);

Step 3: The f_i, L_o and r of each bat are continuously adjusted;

Step 4: The loudness is varied from its maximum constant value to a minimum one.

The position, x_i and the rate of change of the position, v_i of the individual bats are updated throughout the process where the positions x_i^t and velocities v_i^t at a time step t, are computed as follows:

$$f_i = f_{min} + (f_{max} - f_{min})\vartheta \qquad \vartheta \in [0, 1] \quad (15)$$

$$v_i^t = v_i^{t-1} + \left(x_i^t - x^*\right)f_i \quad (16)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (17)$$

Where ϑ is a random vector obtained from a uniform distribution function. The current global best location x^* is then obtained after comparing all locations of all the bats. Since the velocity is given as in (18), change in f_i or λ_i can result in a velocity change.

$$v_i = \lambda_i f_i \quad (18)$$

Algorithm is initialized by assigning a random frequency $f_i \in [f_{max}, f_{min}]$ to bat i. For the local search, as soon as a solution is chosen from the current best solutions, a new solution for each bat is generated locally using random walk.

$$x_{new} = x_{old} + \varepsilon L^t \quad (19)$$

Where ε is a random number that lies between -1 and 1, while L^t is the mean loudness of all bats at time step t. Loudness of each bat decreases as soon as it gets its prey, however the r increases and then loudness can be selected as any value of convenience. Zero loudness indicates that a bat has just found a prey and temporarily stop emitting any sound. This is governed by the following equation:

$$L_i^{t+1} = \varphi L_i^t \qquad 0 < \varphi < 1 \quad (20)$$

ABIA has many other variants like Fuzzy Logic Bat Algorithm (BA), K-Means, chaotic, binary BA, differential operator and levy flights BA and improved BA (Yang & He, 2013). Fig. 1 shows the flowchart of the ABIA search algorithm.

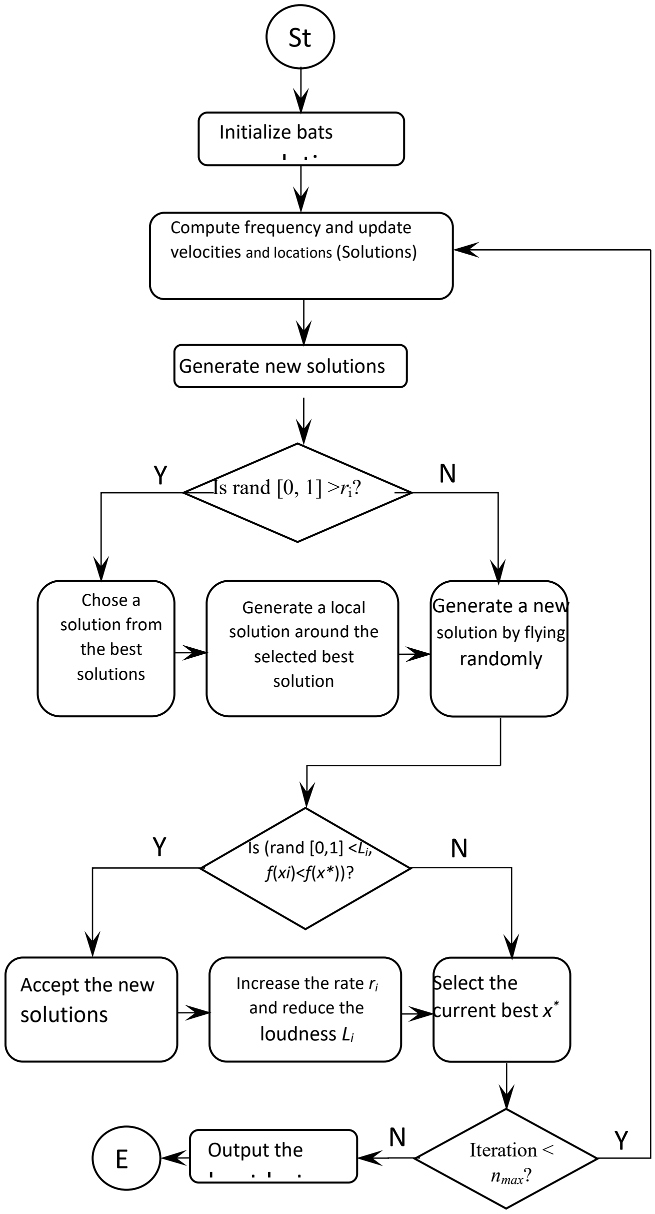

Fig. 1 The flowchart of ABIA technique (Elsisi et al., 2016)

4 TEST SYSTEMS DESCRIPTION

The proposed method is implemented in MATLAB software and simulation is performed using IEEE 57-bus systems, with 30 hybrid thermal-PV generating units test system. The system comprises of 10 solar plants and 20 thermal generating units whose cost coefficients, generation limits and ramp rates are summarized in Table 1. While Table 2 shows the emission cost coefficients of the system with Table 3 showing the PV specification and cost parameters. The average Nigerian solar radiation and temperature profile (fig. 2 and 3) respectively, are used for the simulation. It can be observed from fig. 2 that the solar radiation is negligible from 07:00pm to 7:00am, while maximum radiation level is witnessed at around midday.

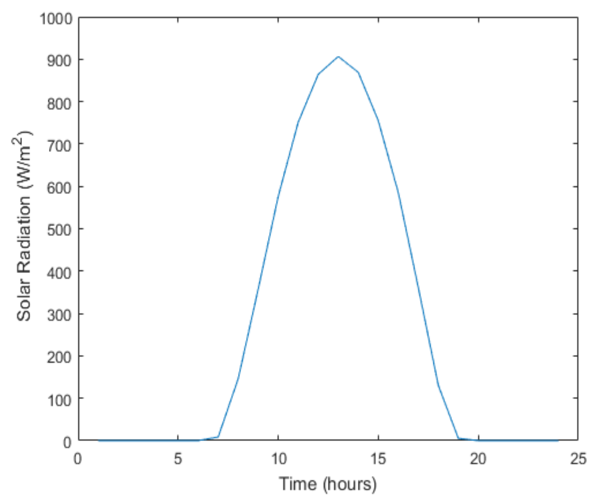

Fig. 2 Solar Radiation Profile

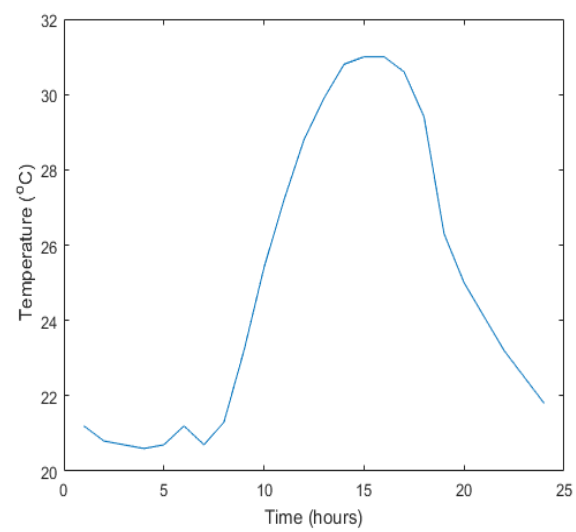

Fig. 3 Temperature profile

Table 1:Table 1. Fuel cost coefficients for 20 thermal generators (Premrudeepreechacham, 2007)

Unit	a_i (\$/h)	b_i (\$/MWh)	c_i (\$/MWh)	d_i (\$/h)	e_i (rad/MW)	P_{Gi}^{min} (MW)	P_{Gi}^{max} (MW)	D_i^{rate} (MW/h)	U_i^{rate} (MW/h)
1	1000	18.19	0.0086	122	0.037	150	600	33	33
2	970	17.26	0.0071	146	0.048	50	200	46	44
3	600	19.8	0.0065	145	0.033	50	200	32	30
4	700	19.1	0.006	133	0.042	50	200	40	42
5	420	18.1	0.00738	125	0.036	50	250	33	32
6	360	19.26	0.00612	135	0.033	20	200	35	35
7	490	17.14	0.0079	130	0.048	25	200	32	30
8	660	18.92	0.00813	123	0.041	50	150	41	41
9	765	18.27	0.00622	112	0.035	50	200	36	34
10	770	18.92	0.00673	124	0.034	30	150	30	30
11	800	17.69	0.0068	142	0.03	100	300	38	38
12	970	16.76	0.0051	136	0.042	100	500	42	40
13	900	18.36	0.0085	129	0.03	40	250	45	45
14	700	18.7	0.00611	112	0.045	20	130	33	33
15	450	18.7	0.00698	133	0.033	25	185	25	25
16	370	14.26	0.00712	128	0.034	20	250	35	35
17	480	19.14	0.0089	125	0.03	30	250	30	30
18	680	18.92	0.00713	125	0.046	30	200	45	45
19	700	18.47	0.00622	135	0.04	40	250	32	30
20	850	19.79	0.00773	115	0.032	30	200	40	42

Table 2. Emission cost coefficients for 20 thermal generators (Premrudeepreechacham, 2007)

Unit	α_i (kg/h)	β_i (kg/MWh)	γ_i (kg/MW²h)	τ_i (kg/h)	ξ_i (rad/MW)
1	4.8	-222	6000	1.31	0.0569
2	4.8	-222	6000	1.31	0.0569
3	7.62	-236	10000	1.31	0.0569
4	5.4	-314	12000	0.9142	0.0454
5	8.5	-189	5000	0.9936	0.0406
6	8.54	-308	8000	1.31	0.0569
7	2.42	-306	1000	0.655	0.02846
8	3.1	-232	13000	0.655	0.02846
9	3.35	-211	15000	0.655	0.02846
10	42.5	-434	28000	0.655	0.02846
11	3.22	-434	22000	0.655	0.02846
12	3.38	-428	22500	0.655	0.02846
13	2.96	-418	30000	0.5035	0.02075
14	5.12	-334	52000	0.5035	0.02075
15	4.96	-355	51000	0.5035	0.02075

16	4.96	-355	51000	0.5035	0.02075
17	1.51	-268	22000	0.5035	0.02075
18	1.51	-266	22200	0.5035	0.02075
19	1.51	-268	22000	0.5035	0.02075
20	1.51	-268	22000	0.5035	0.02075

Table 3. PV specification and cost parameters (Premrudeepreechacham, 2007)

Components	**Characteristics**	**Value**
PV panel	Maximum power	240 W
	Maximum voltage (Vmp)	30.3 V
	Maximum current (Imp)	7.92 A
	Open circuit voltage (Voc)	37.1 V
	Short circuit current (Isc)	8.88 A
	Maximum system voltage	1000 VDC
	Dimension	1.653m x 0.995m x 0.045m
	Air mass at STC	1.5
	Irradiance at STC	1000 W/m^2
	Cell temperature at STC	25°C
	Temperature coefficient	- 0. 25%/°C
Cost parameters	PV panel cost	$ 0.5/W
	Electricity cost	$ 0.85/kWh
	Inflation	9%
	O&M cost	2%

5 SIMULATION RESULTS AND DISCUSSION

To ascertain the effectiveness of the proposed IEED technique, simulations are carried on IEEE 57-bus test system subjected to the hourly load demand profile as depicted in Fig. 4. The load demand is a 24-hour demand with daily average of 1723.5 MW. The load demand profile is divided into four-time intervals; 00:00-06:00 hours, 06:01-12:00 hours, 12:01-18:00 hours and 18:01-23:59 hours whose average load demands are computed as 1500 MW, 2440 MW, 1910 MW and 1044 MW respectively. The system is subjected to the average load demands.

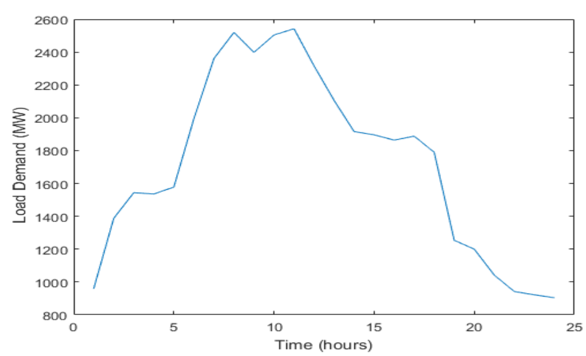

Fig. 4: Load demand profile

The proposed ABIA solved the IEED problem and yielded the optimal dispatch of both thermal and solar power plants as tabulated in Table 4 and shown in Fig. 5.

Table 4. IEED for 30 generating units

Average demand	**1500 MW**	**2440 MW**	**1910 MW**	**1044 MW**
Dispatch Time	00:00 - 06:00	06:01 - 12:00	12:01 - 18:00	18:01 - 23:59
P1	150.000	150.000	150.000	150.000
P2	50.0000	56.5086	50.0000	50.0000
P3	70.8740	91.3535	69.4020	50.0000
P4	60.7496	78.3035	59.4879	50.0000
P5	101.2506	130.5070	99.1477	61.4201
P6	116.1241	152.2566	115.6707	71.6552
P7	86.7872	111.8641	84.9848	52.6468
P8	64.4316	83.0493	63.0934	50.0000
P9	55.5885	71.6508	56.4339	50.0000
P10	55.2271	72.1851	54.0800	33.5013
P11	53.1568	68.5164	52.0528	32.2458
P12	43.8412	56.5089	42.9306	26.5950
P13	47.2501	60.9031	46.2688	40.0000
P14	60.7499	78.3038	59.4882	36.8516
P15	94.4999	122.8059	144.5372	57.3248
P16	114.9383	148.1483	112.5513	69.7253
P17	88.5932	114.1925	86.7532	53.7415
P18	62.5365	80.6067	61.2377	37.9353
P19	60.7501	78.3039	59.4884	40.0000
P20	50.0287	64.4848	48.9897	30.3478
Solar unit commitment (ON/OFF states)	0, 0, 0, 0, 1, 0, 1, 0, 0, 0	1, 1, 0, 1, 1, 0, 1, 1, 1, 0	0, 1, 0, 1, 1, 0, 1, 0, 1, 0	0, 0, 0, 0, 0, 0, 0, 0, 0, 0
Solar share (MW)	12.6201	574.5456	451.3984	0.0000
Power loss (MW)	18.3194	22.9820	17.9900	12.8412
Fuel cost (k$/h)	5.7040	3.0414	4.8254	7.2652
Emission cost (k$/h)	3.5144	1.7740	2.1484	5.7317
Solar cost (k$/h)	0.0508	2.3091	1.5335	0.0000
Total cost (k$/h)	9.2692	7.1245	8.5073	12.9969

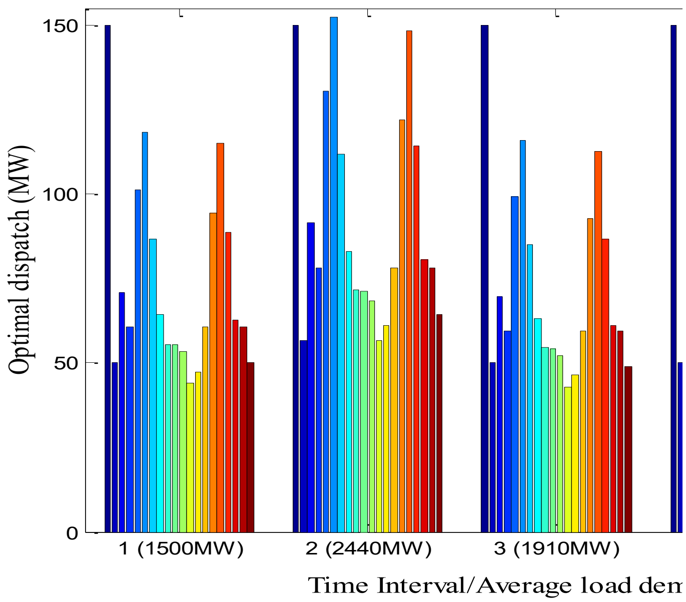

Fig. 5 Optimal dispatch of thermal generators

Fig. 6 shows the convergence of the proposed ABIA while minimizing the IEED objective function. The result gives better convergence when compared with that of Euclidean affine flower pollination algorithm presented in (Shilaja & Rabi, 2017), which took over 200 iterations to converge.

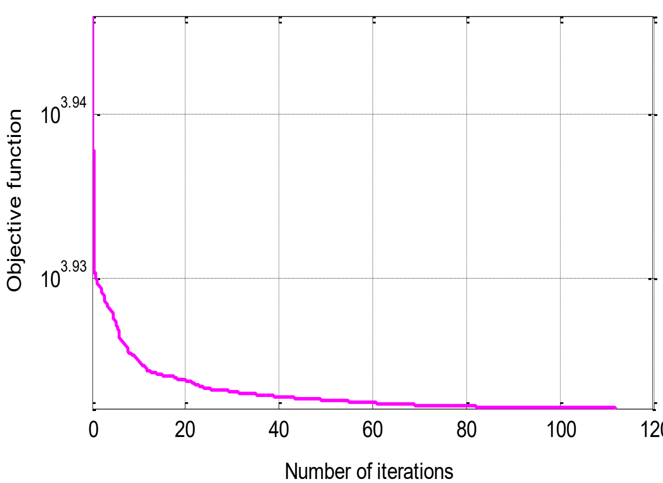

Fig. 6 ABIA convergence on the proposed EED problem

As formulated in the objective function, the solar generators are used to reduce the fuel and emission cost of thermal generators. So, with increase in the solar generation (which is directly related to the available solar radiation and temperature), fuel and emission cost decreases. For instance, during the period 00:00-06:00 with an average demand of 1500 MW, the solar contributed with 12.6201 MW representing 0.84% by optimally operating the 5th and 7th solar units. In the second time interval; 06:01-12:00, the solar plant contributed 574.5456 MW representing 23.5 % of 2440MW average demand. This huge amount of power is obtained by switching ON all the solar units with exception of 3rd, 6th and 10th units due to operational constraints. Within this time interval the fuel and emission cost are minimized to 3.0414 *k$/h* and 1.7740 *k$/h* respectively. However, when all the solar units are turned OFF, the fuel and emission cost are computed to be 7.2652 *k$/h* and 5.7317 *k$/h* respectively. These represent 31.23% and 27.09% reduction in the fuel and emission costs respectively. It can be observed from Fig. 2 that the average solar radiation at 18:01-23:59 is roughly zero, hence the solar power generation at this time interval is zero thereby turning OFF all the units automatically. Hence, the combined fuel and emission cost during this time interval is found to be 12.9969 *k$/h*. It is envisioned in the future work to consider the load demand for each hour instead of average values.

6 CONCLUSION

In this paper, Integrated Economic and Emission Dispatch (IEED) of hybrid thermal-photovoltaic power plants using artificial bat inspired algorithm (BIA) is presented. It entails determining the optimal scheduling (power output) of a number of electricity generating units, to meet the system load, at the lowest possible cost and reduced greenhouse gases emission, subject to transmission and operational constraints. The constraints considered are generation-demand balance, generation limits and ramp rate constraints. The presented technique is designed to take into consideration the availability of solar radiation and temperature of the solar power plant. While thermal power plants are dispatchable, photovoltaic (PV) system is non-dispatchable. Hence, presented technique solved the IEED for optimal active power output of the thermal units in (*kW*) and binary (ON-OFF) states of the PV system. The nonlinearity in the fuel cost function (with valve-point loading effect) of the generators and need for faster convergence inform the choice of ABIA for the proposed IEED. The proposed method is implemented in MATLAB software and simulation is performed using IEEE 57-bus systems, with 30 hybrid thermal-PV generating units test system. From the simulation carried out, the proposed method has calculated the optimal solutions without violating any system constraints. It has been observed that optimizing the solar and thermal power plants has reduced the fuel and emission cost by 31.23% and 27.09% respectively.

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