Efficient use of the Generators for the Environmental Economic Dispatch from the energy system, including solar photovoltaic generation

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Abstract

The classic Economic Dispatch (ED) problem considers only the cost of power generation by thermal generators, often disregarding the safety parameters of the electrical network, environmental costs and especially the importance of predictive maintenance of the generators, when considering environmental costs in the optimization of ED this becomes a multi-objective problem Environmental Economic Dispatch (EED). Considering the global pressure to reduce emissions of pollutants in the atmosphere and environmental sustainability, incorporating the generation of Renewable Energies (RE) or Green Energy in the electricity grid is indispensable. Solar energy is becoming an important part of the power generation portfolio in many regions due to the fast decline in its costs and political incentives that favor the generation of clean energy sources. This article uses the Ant Lion Optimizer (ALO) method to solve the problem and EED restricted to the grid in a hybrid system (thermoelectric and photovoltaic). The results of the optimization problem were simulated in MATLAB. This research included 01 thermoelectric with 06 generators and 13 solar plants.

Keywords: Economic Emission Load Dispatch, Power Plants, Photovoltaic, Ant Lion Algorithm.

1. Introduction

Due to the current energy crisis and the excessive increase in consumption, economic and environmental problems in power generation force electric utilities and energy producers to consider the environmental impact of power generation plants. The Economic Emission Dispatch (EED) was created to minimize the emission of pollutants such as NOx, SOx, Cox particles and others from the thermoelectric plant. Thus, the

objective of the minimum generation cost or the objective of the minimum emission may not be a desirable criterion.
Thus, the evaluation of the economic dispatch of the emission load (EELD) came into question to discover the objective of the minimum generation cost and the minimum emission level at the same time [1],[3],[4],[5].
In this way, we can verify that environmental costs encompass all costs of treatment, elimination and cleaning of existing waste and emissions, including conventional waste disposal and the costs of treating emissions, working materials and maintenance. In addition to the costs of environmental prevention and management (annual costs for preventing waste emissions)[2],[6].
The deployment of renewable energy sources instead of thermal generation has received a lot of attention. This change in moment occurred due to the rapid depletion of fossil fuel reserves, the dramatic increase in fuel prices and the environmental concerns associated with thermal fuels. However, this production has some technical restrictions on its integration into the electrical system. Currently, solar energy has attracted a lot of attention, with promising solar photovoltaic resources [6-8].
Economic dispatch (ED) is a known optimization problem that aims to find an appropriate combination of energy shares from committed generating units that results in minimal cost. There are numerous restrictions involved in the ED problem, such as generator power limits, power balance, prohibited operating zones, ramp rate limits. Several optimization techniques have been reported in the literature to solve the ED problem [9].
In the literature, several optimization techniques based on artificial intelligence (AI) have been proposed to solve the complex problem of ED, for example, genetic algorithms (GA) [10], particle swarm optimization (PSO) [11], artificial neural networks (ANN) [12], evolutionary programming (EP) [13] and search for taboo (TS) [14].
Thermal generating units produce emissions that result in serious environmental impacts [15]. Therefore, along with cost minimization, a significant intent was used to keep emissions to a minimum. A multi-objective DE problem, which involves fuel costs and emissions, is known as the combined emission economic dispatch (CEED). In [16] they solved the CEED problem under the restrictions of energy balance and power generation capacity limits using PSO. In [17], multi-objective particle swarm optimization (MOPSO) was proposed, and they used a diversity preservation mechanism to find the wide range of optimal pareto solutions.
Recently, several evolutionary, heuristic and metaheuristic algorithms have been developed simulating natural phenomena [18]. Here are some examples: In [19], a technique based on particle swarm optimization (PSO) the application of various types of hybrid algorithms is also described in the literature on power systems.
Among them, there are hybrids that combine two or more evolutionary optimization techniques that can improve the results of the optimization employed in economic dispatch (ED) [20], [21]; in [22–24], the artificial bee colony (ABC) multipurpose algorithm method was used to solve the combined issue of issue and economic load dispatch (EELD) using the penalty factor. Just as for the same problem, optimization of the ant colony was used [25], [26]; simulated annealing (SA) [27], [28] applied differential evolution and [29] presented a multi-objective differential evolution algorithm method to solve EELD. In [30–32] he used

a non-dominated genetic classification algorithm (NSGA II) and evolutionary programming to solve multi-objective environmental and economic dispatches.

Cost reduction and ED issuance are treated as a multi-objective optimization problem. This methodology was used in [33–36].

The ED optimization problem has a preponderant role in the modern energy generation system [37], [4]. It consists of correctly programming the electrical generation to reduce operating costs [38], [39].

The proposed model consists of distributing the demand for power generation between renewable and non-renewable sources (hybrid system) among the plants more economically, reducing costs and emissions of polluting gases and maintaining the stability of the electricity grid after the penetration of electricity photovoltaic solar energy [40], [41].

This paper uses a hybrid model composed of several Photo Voltaic (PV) plants and a Thermal plant to optimize the ED problem considering the pollutant emissions in the atmosphere, that means the Environmental Economic Dispatch (EED) problem, minimizing the total cost of fuel and pollutant emissions, in addition to the rational use of the most efficient generators allowing the predictive maintenance of Thermal plant. The Lion Ant-Algorithm (ALO) multi-use optimization metaheuristic was applied to solve the EED problem at Thermal plant composed of 6 (six) Generator Units (GU) and 13 (thirteen) PV plants, in contrast to the one presented in [1], [2], how it's possible see in figure 1. The research is based on the parameters obtained in [3]. Considering the instabilities of the Generation PV system, for security, only 80% of the capacity of PV plants is used, the rest of the demand is generated by the thermal plant. The results of the optimization problem were simulated in MATLAB.

2. Problem Statement

In order to optimization the multicriteria problem EED, two objective functions should be considered: fuel consumption function (F_2) and environmental cost function (F_3) [40]. The objective function coefficients are obtained by curve fitting techniques based on motor performance tests [42].

2.1 Mathematical model of generation by solar power plant (F_1)

The generation representation model in Solar Power Plant (SPP), and described in (1) [43]:

$$F_1(Pgs_j) = P_{rated}\left(1 + (T_{ref} - T_{amb}) * \; alpha\right) * \frac{S_i}{1000} \tag{1}$$

Where:

Prated = rated power;

Tref = reference temperature;

Tamb = room temperature;

alpha = temperature coefficient; and

Si = incident solar radiation.

With SPP used in power generation, the solar energy employed is described in (2) [43]:

$$Ss = \sum_{j=1}^{m} F_1(Pgs_j) x \; Us_j \tag{2}$$

Where, Pgs_j is the energy available at j^{th} SPP and Us_j indicates the status of j^{th} SPP which is 1 (ON) or 0 (OFF). The cost of SPP is given by (3) [43]:

$$Sc = \sum_{j=1}^{m} PUCost_j \; x \; F_1(Pgs_j) \; x \; Us_j \tag{3}$$

where $PUCost_j$ is the unit cost of $\boldsymbol{j^{th}}$ SPP.

2.2 Mathematical model of cost of thermal plants (F_2)

The primary objective of ELD is to determine the optimal distribution of energy demand among the compromised generating units while minimizing the total operating cost while satisfying a set of equality and inequality constraints, that is one of the main tasks of optimization in power systems. Due to environmental responsibility ELD becomes an EELD multicriteria optimization problem, seeking to reduce pollutant gas emissions into the atmosphere [44].

The fuel consumption equation of each generating unit is represented by a quadratic function (4), considering the output power of generator Pi, given in \$ / h, as:

$$f_i(P_i) = a_i + b_i P_i + c_i P_i^2 \tag{4}$$

where a_i, b_i and c_i represent the fuel consumption coefficients of each ith generating unit.

The problem of minimizing the total cost of the thermal plant is represented in (5).

$$Min \; F_2(P_i) = \sum_{i=1}^{N} f_i(P_i) \tag{5}$$

Where N is the total generating units of the thermal plant and P_i the output power of each generating unit. Figure 1 illustrates the fuel consumption curve without effect of the valve point, noting that it is not the representation of the engine efficiency curve.

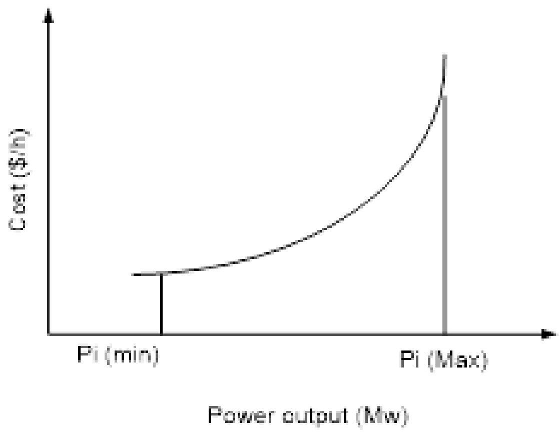

Figure 1. Fuel consumption without valve point effect.

Source: Adapted from [35]

Wire drawing effects, occurring as each steam admission valve in a turbine starts to open, produce a rippling effect on the unit curve. A sharp increase in fuel loss is added to the fuel cost curve due to wire drawing effects when the steam admission valve starts to open. This procedure is named as valve point effect [40].

2.3 Mathematical model of emissions of thermal plants (F_3)

The total emission function of the thermal plant, formulated in (6), relates the emissions with the power generated by each generating unit [45]. This function represents the emission of SO_2 and NO_x in kg / h which can be expressed as follows: [40], [46]:

$$F_3(P_i) = \sum_{i=1}^{N}(\alpha_i + \beta_i P_i + \gamma_i P_i^2) \tag{6}$$

Where d_i, e_i and f_i represent the emission coefficients of each generating unit.

2.4 Economical load dispatch constrains

2.4.1 Equality power balance constraint

Rated power is defined by the lower and upper limits of each generator unit. In (7) the power balance equality constraint is formulated [46], [47]

$$\sum_{i=1}^{n} P_i - P^D - P^L = 0 \tag{7}$$

Where $\boldsymbol{P_i}$ is the nominal power of each generating unit, $\boldsymbol{P^D}$ is the power demand, $\boldsymbol{P^L}$ is the transmission losses. Therefore, the total generation must be equal to the power demand plus the actual losses on the transmission lines, as (8):

$$\sum_{i=1}^{n} P_i = P^D + P^L \tag{8}$$

The total power restriction generated (8) must take into account the generation of SPP, (9) [3].

$$P^D + P^L - \sum_{i=1}^{n} P_i - \sum_{j=1}^{m} Pgs_j \; X \; Us_j = 0 \tag{9}$$

The sizing of the $\boldsymbol{P^L}$ is equal to the sum of the losses versus power, which presents equality constraints on the active and reactive power in each bar, as follows. (10) [48]:

$$P^L = \sum_{i=1}^{n} B_i \, P_i^2 \tag{10}$$

Transmission losses are defined as a function of generator output by deriving the Kron loss coefficients from the Kron loss formula., (11) [49]:

$$P^L = \sum_{i=1}^{n}\sum_{j=1}^{n} P_j \, B_{ij} \, P_j + \sum_{i=1}^{n} B_{oi} \, P_j + B_{oo} \tag{11}$$

Where $\boldsymbol{B_{ij}}$, $\boldsymbol{B_{oi}}$ and $\boldsymbol{B_{oo}}$ are the transmission loss coefficients in the network, n is the number of generators. Coefficients B can be determined with certain precision when actual operating conditions are close to the base case [50].

2.4.2 Generation Constraint

The power of each generating unit is determined by the lower and upper limits as (12) [51]:

$$P_{min.i} \le P_i \le P_{max.i} \tag{12}$$

Where P_i is the output power of each generating unit, $P_{min.i}$ and $P_{max.i}$ is the minimum and maximum power of each generating unit.

Another constraint that must be met in a hybrid system with renewable energy is to use a maximum of 80% of the maximum installed capacity of the SPP, due to its generation instability, as shown in (13) [3]:

$$\sum_{j=1}^{m} Pgs_j \; X \; Us_j \le 0.8 \; x \; SPP \tag{13}$$

2.5 Optimization problem

To this problem, the power generation is calculated by analyzing the installed capacity of the PPS, using a maximum value of 80% of the total generation, then the cost of this power generation in the PPS is calculated, applying function $\boldsymbol{F_1(Pgs_j)}$(j) described in (1). Remaining outstanding demand is resolved by minimizing multicriteria function, (14):

$$Min\ (Pi) = [F_2(Pi), F_3(Pi)] \tag{14}$$

Where ***F2 (Pi), F3 (Pi)*** are the objective functions to be optimized considering the nominal power constraints ***(Pi)*** of each generating unit described in (12).

2.6 Formulation of the incremental cost

The incremental fuel cost formulation ($ / MWh) is described in (15) [26], [46] and shown in Figure 2:

$$IC_i = (2. a_i. P_{gi} + b_i) \tag{15}$$

Where:

IC_i = is incremental fuel cost;

a_i = is actual incremental cost curve;

b_i = is approximated (linear) incremental cost curve;

P_{gi} = is total power generation.

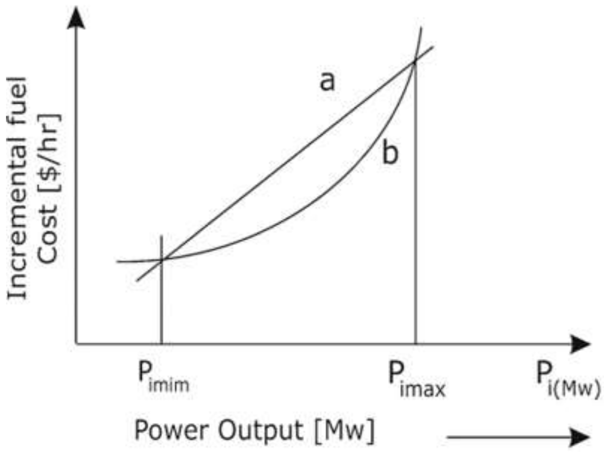

Figure 2. Incremental Cost Curve.

Source:[26]

3. Ant Lion Optimization Technique

In 2015 a nature-inspired algorithm called Ant Lion Optimizer (ALO) was proposed [52]. The main methodology of the ALO algorithm stems from the foraging strategy of antlion larvae. It is also a population algorithm that simulates antlion hunting behavior. It uses five steps: random walk; trap building; catching ants and prey; prey removal and restoration of traps [52].

The larval and adult stages are two important stages in the life cycle of ALO. Antlion hunts in the larval stage and breeds in the adult stage. The larval period is the basis for the ALO algorithm. The antlion digs the cone-shaped pit in the sand, following a circular path and removing the sand with its jaws. After building the trap, the larva waits for the prey. Trap size varies with hunger level, antlion and moon size [53].

The ALO algorithm can also be used to optimize the EELD problem [54]. This algorithm is effectively employed to solve various types of test functions (non-modal, multimodal and composite). ALO capabilities are converging to the overall solution at a rapid convergence rate due to the use of the roulette selection method, which also deals with continuous and discrete optimization problems.

Comparing ALO with different problems and applications validates its technique with better performance compared to other optimization algorithms such as GA, PSO, DE, AS, ABC, TSA, and HSA.

ALO simulates the interactions between ants and antlion in the trap, where they are most efficient. According to the undetermined movement of ants in the wild when searching for food, a random path is chosen; To model the movement of ants, we use the following mathematical model (16) [52]:

$$X(t) = [0, cumsum(2r(t\_1\ ) - 1), cumsum(2r(t_2) - 1), \dots, cumsum(2r(t_n) - 1)\ ] \quad (16)$$

Where $cumsum$ computes the accumulated total, n is the maximum amount of iterations, t shows the current iteration, and $r(t_n)$ is the stochastic function described in (17) [1], [53]:

$$r(t) = \begin{cases} 1\ if\ rand > 0.5 \\ 0\ if\ otherwise \end{cases} \quad (17)$$

Where **t** displays the current random iteration and ***rand*** is a random number generated with uniform distribution in the range of (0.1).

To preserve the random iteration within the search range and to stop ants from crossing the path should be normalized according to (18) [54]:

$$X_i^t = \frac{(X_i^t - a_i) \times (d_i^t - c_i^t)}{b_i - a_i} + c_i^t \quad (18)$$

Where $\boldsymbol{a_i}$ e $\boldsymbol{b_i}$ is the minimum and maximum of random iterations $\boldsymbol{i^{th}}$ variable, $\boldsymbol{c_i^t}$ e $\boldsymbol{d_i^t}$ indicates the minimum and maximum $\boldsymbol{i^{th}}$ iteration in $\boldsymbol{t^{th}}$ variable.

To describe ant capture, are used (19 and 20) [55]:

$$c_m^t = Ant - lion_n^t - c^t \quad (19)$$

$$d_m^t = Ant - lion_n^t - d^t \quad (20)$$

The most suitable antlion is the construction of the trap since the roulette method is used.

To mathematically model this hypothesis, are proposed (21 e 22) [53]:

$$c^t = \frac{c^t}{I} \quad (21)$$

$$d^t = \frac{d^t}{I} \quad (22)$$

Where, $\boldsymbol{c^t}$ is the minimum of all variables at t^{th} iteration, and $\boldsymbol{d^t}$ indicates the vector including the maximum of all variables at t^{th} iteration and I is a ratio, defined in (23).

$$I = 10^w\ (t/S) \quad (23)$$

Where, $\boldsymbol{t}$ is the current iteration, $\boldsymbol{S}$ is the maximum number of iterations and **w** is a constant whose value is given by (24) [55]:

$$w = \begin{cases} 2\ if\ t > 0.1S \\ 3\ if\ t > 0.5S \\ 4\ if\ t > 0.75S \\ 5\ if\ t > 0.9S \\ 6\ if\ t > 0.9S \end{cases} \quad (24)$$

To capture ants by ants and rebuild their trap can be described by the mathematical sentence (25) [36]:

$$Antlion_j^t = Ant_i^t, if\ f(Ant_i^t) > f(Antlion_j^t) \quad (25)$$

On what $\boldsymbol{Antlion_i^t}$ indicates the position $\boldsymbol{j^{th}}$ to antlion selected in the iteration, $\boldsymbol{Ant_i^t}$ displays ant position in iteration and **t** shows current iteration.

Therefore, it is assumed that all ants walk randomly around an antlion selected by roulette and elitism simultaneously, as (26) [53]:

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \tag{26}$$

Where $\boldsymbol{R_A^t}$ is the random trajectory around the antlion selected by the roulette method in $\boldsymbol{t^{th}}$, $\boldsymbol{R_E^t}$ is the random trajectory around the elitism of $\boldsymbol{t^{th}}$ e $\boldsymbol{Ant_i^t}$ indicates the position $\boldsymbol{i^{th}}$ ant on $\boldsymbol{t^{th}}$ iteration.

4. Solving Eed Problem with Alo

The steps for an ALO optimization application are as follows:

Step 1. The ant set is initialized with random values and are the main research agents in ALO.

Step 2. The fitness value of each ant is assessed using an objective function (Eq. 14) in each iteration.

Step 3. Ants move around the research space using random walks through the antlions.

Step 4. The position of the ants is evaluated in each iteration and reallocating the ones that are in the best position.

Step 5. There is an antlion assigned to each ant and updates its position if the ant becomes more fit.

Step 6. There is also an elite antlion that affects the movement of ants, regardless of their distance.

Step 7. If an antlion becomes better than the elite, it will be replaced by the elite.

Step 8. Steps 2 through 7 are performed repeatedly until a final criterion is satisfied.

Step 9. The position and fitness value of the elite antlion are returned as the best estimate for the overall optimization.

The random trajectory of ants using (16). In addition to the ants, we assume that antlions are also hidden somewhere in the search space, to save their positions and aptitude values, the following matrix are used (27, 28, 29 and 30) [53]:

$$M_{Ant} = \begin{bmatrix} Ant_{1,1} & Ant_{1,2} & Ant_{1,3} & \dots & Ant_{1,d} \\ Ant_{2,1} & Ant_{2,2} & Ant_{2,3} & \dots & Ant_{2,d} \\ \dots & \dots & \dots & \dots & \\ Ant_{n,1} & \dots & \cdots & \dots & Ant_{n,d} \end{bmatrix}_{n \times d} \tag{27}$$

Where $\mathbf{M_{Ant}}$ is the matrix that stores each antlion position, $\mathbf{AL_{i,j}}$ displays the value of $\mathbf{j^{th}}$ dimension of $\mathbf{i^{th}}$ antlion, **n** is the number of antlions and **d** is the number of variables.

To evaluate each ant (ie generating units), the following objective functions, described in (4) and (5), where they are used during optimization and the matrix of (28) stores the value of attributes of all ants:

$$M_{OA} = \begin{bmatrix} f([Ant_{1,1}, Ant_{1,2}, \cdots, Ant_{1,d}]) \\ f([Ant_{2,1}, Ant_{2,2}, \cdots, Ant_{2,d}]) \\ \vdots \\ f([Ant_{n,1}, Ant_{n,2}, \cdots, Ant_{n,d}]) \end{bmatrix} \tag{28}$$

Where M_{OA} is the matrix that stores the suitability of each ant, $\boldsymbol{Ant_{i,j}}$ displays the value of $\boldsymbol{j^{th}}$ dimension of $\boldsymbol{i^{th}}$, $\boldsymbol{n}$ is the number of ants and $\boldsymbol{f}$ is the objective function.

To optimize cost and power generation was used (29) e (30):

$$M_{AL} = \begin{bmatrix} AL_{1,1} & AL_{1,2} & AL_{1,3} & \dots & AL_{1,d} \\ AL_{2,1} & AL_{2,2} & AL_{2,3} & \dots & AL_{2,d} \\ \dots & \dots & \dots & \dots & \\ AL_{n,1} & \dots & \cdots & \dots & AL_{n,d} \end{bmatrix}_{n \times d} \quad (29)$$

Where $\boldsymbol{M_{AL}}$ stores the position of each ant, $\boldsymbol{AL_{i,j}}$ displays ALO dimension value $\boldsymbol{j}$, $\boldsymbol{n}$ is the number of ants and $\boldsymbol{d}$ is the number of variables (generators).

$$M_{OAL} = \begin{bmatrix} f([AL_{1,1}, AL_{1,2}, \cdots, AL_{1,d}]) \\ f([AL_{2,1}, AL_{2,2}, \cdots, AL_{2,d}]) \\ \vdots \\ f([AL_{n,1}, AL_{n,2}, \cdots, AL_{n,d}]) \end{bmatrix} \quad (30)$$

Where $\boldsymbol{M_{OAL}}$ stores the attributes of each ALO, $\boldsymbol{AL_{i,j}}$ shows the value of $\boldsymbol{j^{th}}$ dimension of $\boldsymbol{j^{th}}$ ALO, $\boldsymbol{n}$ is the number of ants and $\boldsymbol{f}$ is the objective function of optimization.

The solution presented involves the number of generations of the system that will be optimized, resulting in the minimization of costs and emissions of the pollutant gases, as shown by (14), and complying with the restrictions of (7 - 12).

Equation (14) is applied to evaluate EED performance even though optimal costs and emissions are achieved. For inequality constraints analogous to other techniques, when the solutions reached for any iteration are out of bounds, ALO indicates the boundary values, while for equality constraints, when violated the penalty factor of 1000 is implemented and incorporated into the function. According to (14) [53]. The algorithm will continue until the maximum iteration and best results are found.

The flowchart of the ALO method is shown in Figure 3.

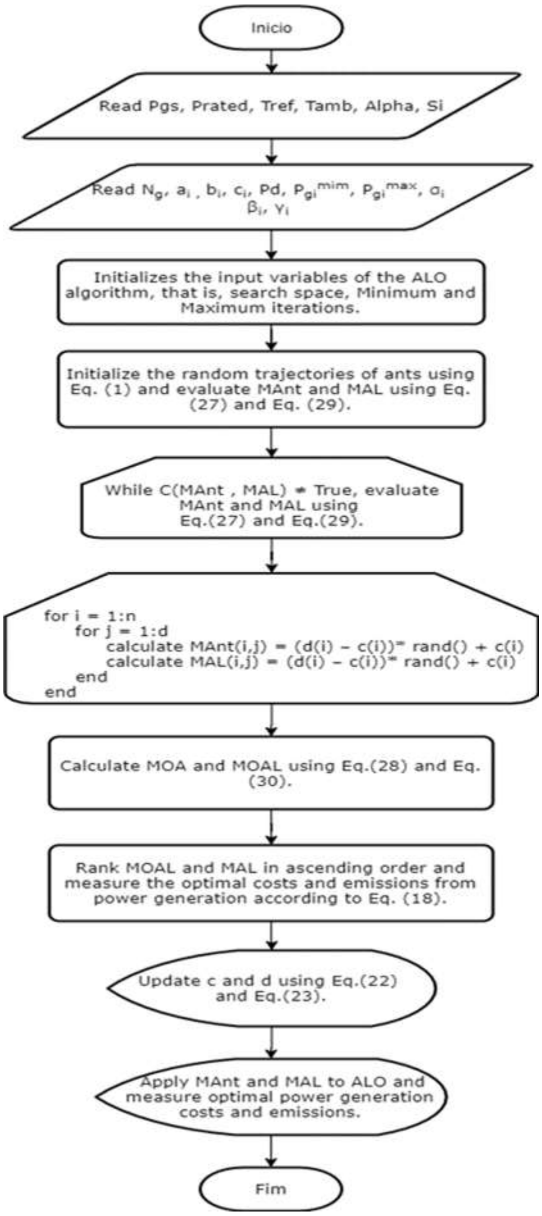

Figure 3. Flow chart of ALO for economic load dispatch problem.

Source: Adapted from [36].

5. Case Study: IEEE 6-units test system and 13 solar plants

In this section, the proposed model considers a demand of 100% to be met, and for security reasons 80% or less of the SPP's capacity will be used, due to the instability of the generation of the SPP, the rest of the demand will be met by TP. In the percentage to be met by the TP, optimization of the EED problem is applied, considering a test system with 6 units to supply the need for demand [3]. The TP selected for the case study consists of six (06) generating units, presents fuel cost coefficients (a, b and c) as well minimum (Pmin) and maximum (Pmax) power limits whereas are shown in Table 1 [3].

Table 1. Fuel cost coefficients for each TP generating unit.

Machine Nº.	α ($/MW²h)	β ($/MW h)	c ($/h)	Pmin (MW)	Pmax (MW)
1	0,15247	38,53973	756,79886	10	125
2	0,10587	46,15916	451,32513	10	150
3	0,02803	40,39655	1049,32513	40	250
4	0,03546	38,30553	1243,5311	35	210
5	0,02111	36,32782	1658,5696	130	325
6	0,01799	38,27041	1353,27041	125	315

Source: [33], [56–58].

Table 2 shows the emission coefficients of the TP units (α, β and γ) [33], [56–58].

Table 2. Emission coefficients of the plants.

Machine No.	α (kg/MW² h)	β (kg/MW h)	y (kg/h)
1	0,00419	0,32767	13,85932
2	0,00419	0,32767	13,85932
3	0,00683	-0,54551	40,2669
4	0,00683	-0,54551	40,2669
5	0,00461	-0,51116	42,89553
6	0,00461	-0,51116	42,89553

Source: [33], [56–58].

Table 3 presents the power ratings and unit costs of different SPP, approximated to be within the range provided.

Table 3. Power ratings and rates per unit of SPP.

Plant	Prated (Mw)	Unit Rate ($/kw h)
1	20	0,22
2	25	0,23
3	25	0,23
4	30	0,24
5	30	0,24
6	35	0,25
7	35	0,26
8	40	0,27
9	40	0,27
10	40	0,28

11	40	0,28
12	40	0,28
13	40	0,28

Source: [3].

Table 4 encompasses global solar radiation as well as temperature and load profiles of Islamabad for the 17th day of July 2012. The global solar radiation data has been generated using Geospatial Toolkit, data related to power demand of Islamabad region has been taken from IESCO [3] and temperature profile has been taken from [59]. The 17th day of July has been selected arbitrarily from the only available demand data of July 2012.

Table 4. Solar Radiation, Energy Demand and Temperature.

Time	Global Solar Radiation (W/m^2)	Power Demand (MW)	Temperature (°C)
01:00	0	965	30
02:00	0	1142	29
03:00	0	1177	28
04:00	0	1198	28
05:00	5,4	1153	28
06:00	101	1136	-
07:00	253,7	1138	29
08:00	541,2	1060	31
09:00	530,4	1155	33
10:00	793,9	1244	34
11:00	1078	1088	35
12:00	1125,6	1240	36
13:00	1013,5	1135	37
14:00	848,2	1318	37
15:00	726,7	1074	37
16:00	654	1190	38
17:00	392,9	1276	38
18:00	215,1	1154	37
19:00	38,5	1333	35
20:00	0	1322	34
21:00	0	1269	34
22:00	0	1139	33
23:00	0	1202	32
00:00	0	1291	-

Source: [3].

6. Analysis and discussion of results

This section shows the results of the proposed ALO, comparing the simulations obtained in Khan [42]. To simulate the proposed model, a computer with MATLAB software version: 8.5.0.197613 (R2015a), processor Intel® Core (TM) i3-6006U CPU@ 2.00 GHz, 4.00 GB of system RAM. Control settings used for ALO were: C1, C2 = 2; r1, r2 = random numbers between 0 and 1; Maximum number of iterations =

1500.

The table 5, introduce the comparative result of the simulation at 10:00 am, reaching a total demand of 1244MW of power.

Table 5. Results of comparison with solar energy for demand of 1244 MW at 10:00h.

	UG	Khan [3]	New Solution
Thermal Generation	**P1(MW)**	120.4479	124.0906
	P2(MW)	92.2947	0
	P3(MW)	155.8062	249.1612
	P4(MW)	76.4153	34.9182
	P5(MW)	257.9089	261.5891
	P6(MW)	302.2846	305.7141
Total Thermal Power (MW)		1005.16	975.47
Solar Power share (MW)		238.83	269.64
Total Power (MW)		1,243.98	1,245.12
Fuel cost($/h)		52,626.00	50,709.57

The comparison (table 5), presents the shutdown of the P2 UG, do not compromising the fulfillment of the demand specified for the time, enabling predictive maintenance, and using the other UGs at their optimum powers, reaching a better efficiency of the Generators and still obtaining a reduction in fuel costs of $ 1,916.43 equivalent to 3.64%.

The table 6, introduce the comparative simulation result at 11:00 am, reaching a total demand of 1244 MW of power.

Table 6. Results of comparison with solar energy for demand of 1088 MW at 11:00h.

	UG	Khan [3]	New Solution
Thermal Generation	**P1 (MW)**	10,1062	0
	P2 (MW)	10	0
	P3 (MW)	99,1	238,5633
	P4 (MW)	168,682	34,9181

	P5 (MW)	235,8781	277,4756
	P6 (MW)	246,7809	175,2128
Total Thermal Power (MW)		770,5472	726,1700
Solar Power share (MW)		317,47	364,66
Total Power (MW)		1.088,02	1.090,83
Fuel cost($/h)		39.426,00	36.884,04

The comparison (table 6), introduce the shutdown of the P1 and P2 UGs, do not compromising the fulfillment of the demand specified for the time, enabling their predictive maintenance, and using the other UGs at their optimum powers, reaching a better efficiency of the Generators and still obtaining a reduction in fuel costs of $ 2,541.96 equivalent to 6.45%.

The table 7, introduce the comparative simulation result at 12:00, reaching total demand of 1240 MW of power.

Table 7. Results of comparison with solar energy for demand of 1240 MW at 12:00h.

	UG	Khan [3]	New Solution
Thermal Generation	**P1 (MW)**	10	0,0000
	P2 (MW)	10,2191	0,0000
	P3 (MW)	194,9316	246,4608
	P4 (MW)	177,4014	34,9182
	P5 (MW)	224,8683	314,3224
	P6 (MW)	303,5647	271,7419
Total Thermal Power (MW)		920,9851	867,4433
Solar Power share (MW)		319,11	379,21
Total Power (MW)		1.240,09	1.246,66
Fuel cost($/h)		46.762,00	43.579,69

The comparison (table 8), presents the shutdown of UGs P1 and P2, do not compromising the fulfillment of the demand specified for the time, enabling their predictive maintenance, and using the other UGs at their optimum powers, reaching a better efficiency of the Generators, and still getting a reduction in fuel costs of $ 3,182.31 equivalent to 6.81%.

The table 8, introduce comparative result of the simulation at 13:00, reaching a total demand of 1135 MW of power.

Table 8. Results of comparison with solar energy for demand of 1135 MW at 13:00h.

	UG	Khan [3]	New Solution
Thermal Generation	P1 (MW)	10,8593	0
	P2 (MW)	118,1312	0
	P3 (MW)	147,9272	161,7401
	P4 (MW)	186,3632	34,9181
	P5 (MW)	150,7713	324,0428
	P6 (MW)	221,0182	283,7145
Total Thermal Power (MW)		835,0704	804,4156
Solar Power share (MW)		300,10	340,06
Total Power (MW)		1.135,17	1.144,47
Fuel cost($/h)		44.136,00	40.249,85

The comparison (table 8), presents the shutdown of UGs P1 and P2, do not compromising the fulfillment of the demand specified for the time, enabling their predictive maintenance, and using the other UGs at their optimum powers, reaching a better efficiency of the Generators and still getting a reduction in fuel costs of $ 3,886.15 equivalent to 8.8%.

The table 9, introduce the comparative result of the simulation at 14:00 pm, reaching a total demand of 1318 MW of power.

Table 9. Results of comparison with solar energy for demand of 1318 MW at 14:00h.

	UG	Khan [3]	New Solution
Thermal Generation	P1 (MW)	65,2834	114,4776
	P2 (MW)	97,2893	0
	P3 (MW)	250	246,3528
	P4 (MW)	107,6407	34,9181
	P5 (MW)	252,7949	325,4644
	P6 (MW)	297,7576	315,2501
Total Thermal Power		1070,7659	1036,4632

(MW)		
Solar Power share (MW)	247,76	284,59
Total Power (MW)	1.318,52	1.321,06
Fuel cost($/h)	55.082,00	53.420,49

The comparison (table 9), presents the shutdown of the P2 UG, do not compromising the fulfillment of the demand specified for the time, enabling predictive maintenance, and using the other UGs at their optimum powers, reaching a better efficiency of the Generators and still obtaining a reduction in fuel costs of $ 1,661.51 equivalent to 3.02%.

The table 10, introduce the comparative result of the simulation at 15:00 pm, reaching a total demand of 1074 MW of power.

Table 10. Results of comparison with solar energy for demand of 1074 MW at 15:00h.

	UG	Khan [3]	New Solution
Thermal Generation	P1 (MW)	82,7064	0
	P2 (MW)	60,696	0
	P3 (MW)	249,2579	216,6089
	P4 (MW)	96,2554	34,9181
	P5 (MW)	182,7257	320,7596
	P6 (MW)	190,6486	265,5584
Total Thermal Power (MW)		862,29	837,8452
Solar Power share (MW)		211,76	243,83
Total Power (MW)		1.074,05	1.081,67
Fuel cost($/h)		45.057,00	42.010,04

The comparison (table 10), presents the shutdown of the P1 and P2 UGs, do not compromising the fulfillment of the demand specified for the time, enabling their predictive maintenance, and using the other UGs at their optimum powers, reaching a better efficiency of the Generator, and still obtaining a reduction in fuel costs of $ 3,046.96 equivalent to 6.76%. The table XI introduce the comparative of power generation from Thermal plant is presented, among Khan's [42] simulations using PSO and the new solution using ALO and turning off the UGs not necessary to reach demand.

Table 11. Comparison of the use of thermal power

	Total Thermal Power (MW) – Khan [3]	Total Thermal Power (MW) – New Solution
10:00 hours	1005,16	975,47
11:00 hours	770,55	726,17
12:00 hours	920,99	867,44
13:00 hours	835,07	804,42
14:00 hours	1070,77	1036,46
15:00 hours	862,29	837,85

Observed in Table 11, that at all specified times, the new proposal uses the smallest energy generation from Thermal plant.

The graphic of Figure 4 shows off the power generation comparison introduced in table 11.

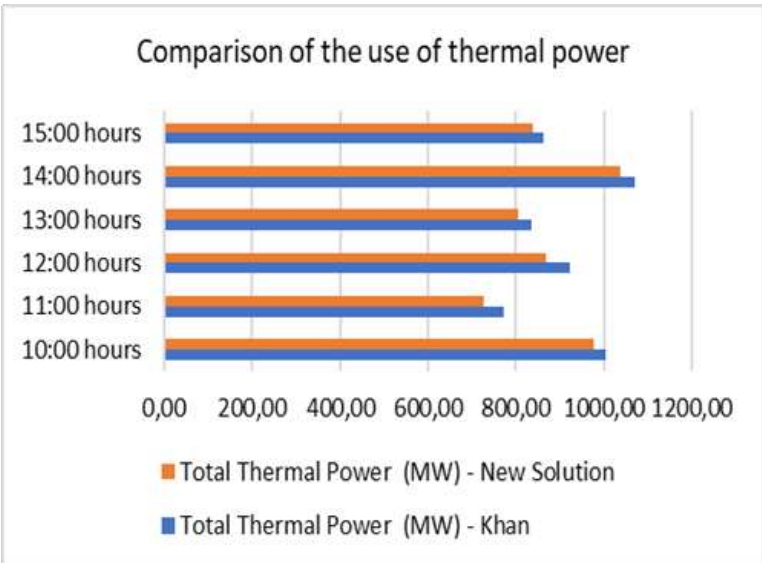

Figure 4. Thermal power generation comparison

The table 12 presents a power generation comparison of PV plants, among Khan's simulations using PSO and the new solution using ALO and turning off the UGs that are not necessary to reach the demand.

Table 12. Comparison of the use of solar power

	Total Solar Power (MW) Khan [3]	Total Solar Power (MW) New Solution
10:00 hours	238,83	269,64
11:00 hours	317,47	364,66
12:00 hours	319,11	379,21
13:00 hours	300,10	340,06
14:00 hours	247,76	284,59
15:00 hours	211,76	243,83

Observed in Table 12, that at all specified times, the new proposal uses the largest energy generation of PV plants.

The graph of Figure 5 demonstrates the power generation comparison presented in table 12.

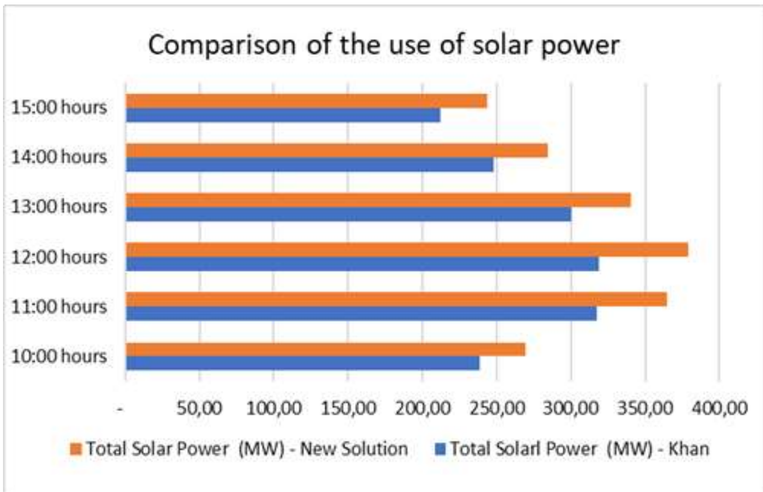

Figure 5. Solar power generation comparison

Tables 8, 9 and 15 show the best results of the ALO simulation to optimize the EED problem. Table 8 shows the power values generated by each solar plant for the **16 hours**, meeting a demand of 1190 MW de power.

Table 13. Power of each Solar unit.

Plant	Power (MW)
1	9.93348
2	12.4168
3	12.4168
4	14.9002
5	14.9002

6	17.3836
7	17.3836
8	19.867
9	19.867
10	19.867
11	19.867
12	19.867
13	19.867
Total	**218,5365**

Source: Authors, (2021).

The Table 14 shows off that the total power generated (218,5365 MW / h) corresponds to 80% of the SPP's capacity due to factors characteristic of solar generation that cause instability in the system. The table 14 introduce the optimal power values for each generating unit defined by ALO.

Table 14. Optimal power of each generating unit.

Machine No.	Power (MW)
1	106.863464
2	0,00
3	234.657978
4	34.9181698
5	313.262103
6	284.112469
Total	973.814185

Source: Authors, (2020).

Table 15 shows the emission values for each generating unit defined by ALO.

Table 15. Volume of emissions from each generating unit.

Machine No.	Emissões (m^3)
1	96.724233
2	0,00
3	288.348251
4	29.5463619
5	335.162274
6	269.662308
Total	**1019.44343**

Source: Authors, (2021).

The total generation (solar + thermal energy) obtained by the ALO algorithm is 1193,3128 Mw, to meet a demand of 1190 Mw, this excess value is to compensate for transmission losses.

It is noted that the proposed algorithm is meeting the defined restrictions. For example, the thermal generation values of each generating unit are within the restriction limits, so that the sharing of solar energy obeys the limits established by the demands required for the time. The reduction costs are consistent with the respective thermal and solar generation performances.

The algorithm increases or decreases the contribution of solar energy based on available radiation and temperature every hour of the day, making the hybrid system more efficient.

In Figure 6, the Pareto graph of the multicriteria problem of cost function and emission function is displayed.

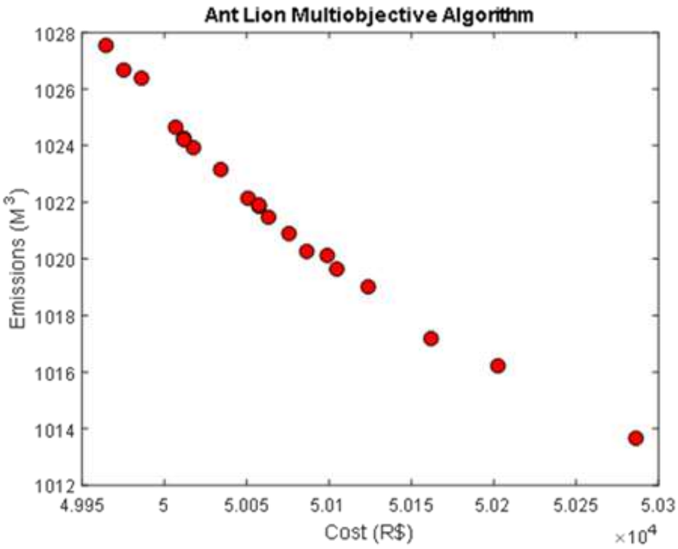

Figure 6. Pareto Chart

Source: Authors, (2021).

In Figure 7 the power graph of the generating unit is displayed.

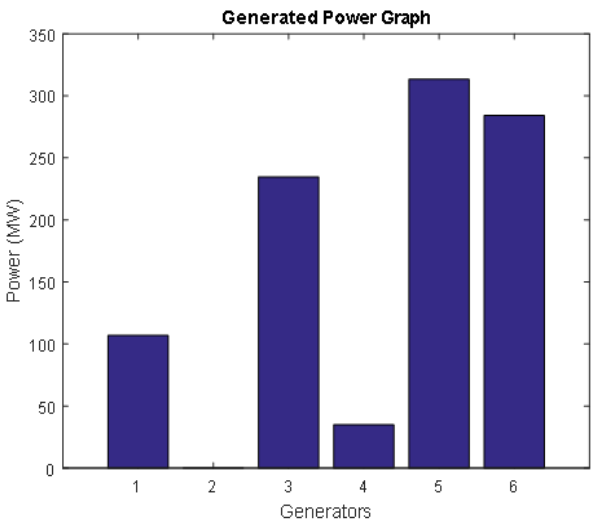

Figure 7. The power graph of the generating unit.

Source: Authors, (2021).

In Figure 8 presents the cost graph of the electrical production of each thermal unit.

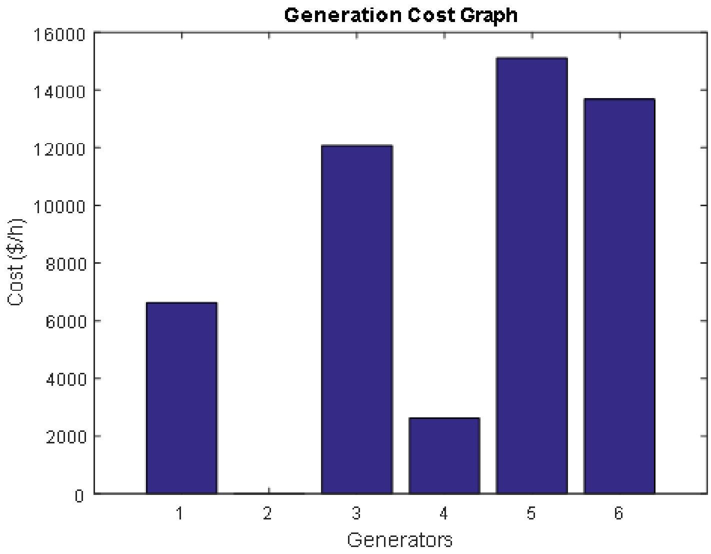

Figure 8. Cost graph of thermal plants.

Source: Authors, (2021).

In Figure 9 shows the emission graph of each thermal unit.

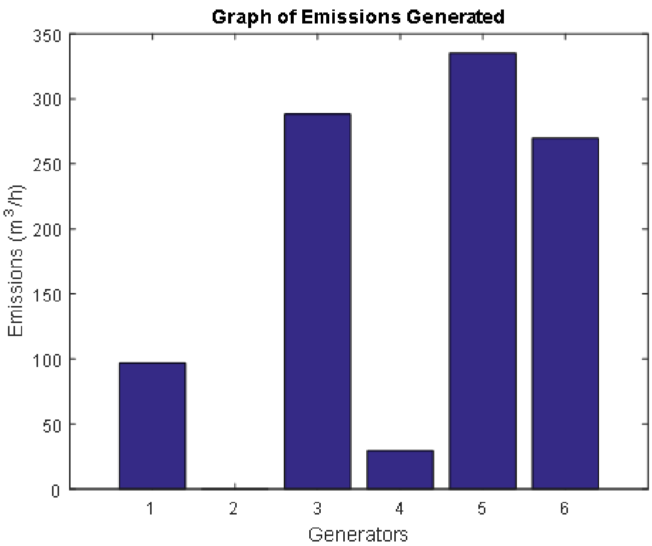

Figure 9. Emissions graph of thermal units.

Source: Authors, (2021).

The graph in Figure 10 shows the power of each solar plant considering only the most efficient ones.

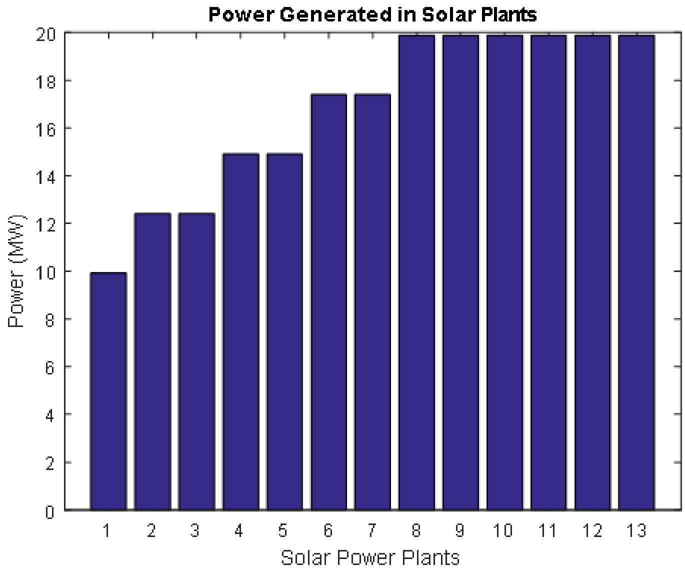

Figure 10. Generation of solar plants

Source: Authors, (2021).

7. Conclusion

Providing reliable and cheap electricity generation has been a significant research objective for decades, so the model proposed in this work aims to solve the EED optimization problem using a hybrid system of PV and Thermoelectric plants. By opting for a greater participation of photovoltaic plants in meeting the demand for energy, a cleaner production is obtained with less environmental impact, contributing to lower volumes of pollutants released into the atmosphere. The comparison with the results of the KHAN simulations, which uses PSO, and a new proposal that uses ALO simultaneously with the shutdowns of UGs that do not compromise to meet demand in the specified time, showed an average reduction of 5.91% in fuel costs.

The algorithm successfully converged and solved the EED optimization problem without violating any restrictions, including energy loss. The simulation results demonstrate a sustainable operation of electricity and its effectiveness at an optimized cost, demonstrating the identification and integration with the adopted System. To future work, we intend to investigate the EED problem and the implementation of the proposed model in hybrid systems (wind, solar and thermal) for power generation.

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9. References

[1] P. Yao e H. Wang, "Dynamic Adaptive Ant Lion Optimizer applied to route planning for unmanned aerial vehicle", *Soft Comput.*, vol. 21, nº 18, p. 5475–5488, 2017.

[2] W. Yamany, A. Tharwat, M. F. Hassanin, T. Gaber, A. E. Hassanien, e T.-H. Kim, "A new multi-layer perceptrons trainer based on ant lion optimization algorithm", in *2015 Fourth international conference on information science and industrial applications (ISI)*, 2015, p. 40–45.

[3] N. A. Khan *et al.*, "Combined emission economic dispatch of power system including solar photo voltaic generation", *Energy Convers. Manag.*, vol. 92, p. 82–91, 2015.

[4] A. Bhattacharya e P. K. Chattopadhyay, "Solving economic emission load dispatch problems using hybrid differential evolution", *Appl. Soft Comput.*, vol. 11, nº 2, p. 2526–2537, 2011.

[5] K. Bhattacharjee, A. Bhattacharya, e S. Halder nee Dey, "Solution of Economic Emission Load Dispatch problems of power systems by Real Coded Chemical Reaction algorithm", *Int. J. Electr. Power Energy Syst.*, vol. 59, p. 176–187, jul. 2014, doi: 10.1016/j.ijepes.2014.02.006.

[6] C. R. C. Rodríguez e G. M. Jannuzzi, "Mecanismos regulatórios, tarifários e econômicos na geração distribuída: o caso dos sistemas fotovoltaicos conectados à rede", *Universidade Estadual Camp. Camp.*, 2002.

[7] M. H. R. Nascimento, M. V. A. Nunes, J. L. M. Rodríguez, J. C. Leite, e J. A. B. Junior, "New solution for resolution of the Economic Load Dispatch by different mathematical optimization methods turning off the less efficient generators", *J. Eng. Tecnol. Ind. Apl.*, vol. 3, p. 10, 2017.

[8] F. RODRIGUES, "Programação da contratação de energia considerando geração distribuída no novo modelo do setor elétrico brasileiro", *Rio Jan. UFRJ*, 2006.

[9] A. J. Wood, B. F. Wollenberg, e G. B. Sheblé, *Power generation, operation, and control*. John Wiley & Sons, 2013.

[10] C.-L. Chiang, "Genetic-based algorithm for power economic load dispatch", *IET Gener. Transm. Distrib.*, vol. 1, nº 2, p. 261–269, 2007.

[11] D. N. Jeyakumar, T. Jayabarathi, e T. Raghunathan, "Particle swarm optimization for various types of economic dispatch problems", *Int. J. Electr. Power Energy Syst.*, vol. 28, nº 1, p. 36–42, 2006.

[12] K. Y. Lee, A. Sode-Yome, e J. H. Park, "Adaptive Hopfield neural networks for economic load dispatch", *IEEE Trans. Power Syst.*, vol. 13, nº 2, p. 519–526, 1998.

[13] Y.-M. Park, J.-R. Won, e J.-B. Park, "A new approach to economic load dispatch based on improved evolutionary programming", *Eng. Intell. Syst. Electr. Eng. Commun.*, vol. 6, nº 2, p. 103–110, 1998.

[14] A. H. Mantawy, S. A. Soliman, e M. E. El-Hawary, "A new tabu search algorithm for the long-term hydro scheduling problem", in *LESCOPE'02. 2002 Large Engineering Systems Conference on Power Engineering. Conference Proceedings*, 2002, p. 29–34.

[15] M. T. Brown e S. Ulgiati, "Emergy evaluations and environmental loading of electricity production systems", *J. Clean. Prod.*, vol. 10, nº 4, p. 321–334, 2002.

[16] A. I. S. Kumar, K. Dhanushkodi, J. J. Kumar, e C. K. C. Paul, "Particle swarm optimization solution to emission and economic dispatch problem", in *TENCON 2003. Conference on Convergent Technologies for Asia-Pacific Region*, 2003, vol. 1, p. 435–439.

[17]Z. Bo e C. Yi-Jia, “Multiple objective particle swarm optimization technique for economic load dispatch”, *J. Zhejiang Univ.-Sci. A*, vol. 6, nº 5, p. 420–427, 2005.

[18]M. A. Rufino, J. S. Siqueira, e A. O. Araújo, “Gestão ambiental: uma análise dos custos das empresas distribuidoras de energia elétrica”, *Rev. Contab. UFBA*, vol. 9, nº 3, 2015.

[19]T. de Fátima Araújo e W. Uturbey, “Performance assessment of PSO, DE and hybrid PSO–DE algorithms when applied to the dispatch of generation and demand”, *Int. J. Electr. Power Energy Syst.*, vol. 47, p. 205–217, 2013.

[20]T. O. Ting, M. V. C. Rao, e C. K. Loo, “A novel approach for unit commitment problem via an effective hybrid particle swarm optimization”, *IEEE Trans. Power Syst.*, vol. 21, nº 1, p. 411–418, 2006.

[21]A. Y. Saber, “Economic dispatch using particle swarm optimization with bacterial foraging effect”, *Int. J. Electr. Power Energy Syst.*, vol. 34, nº 1, p. 38–46, 2012.

[22]F. S. Lobato, “Multi-objective optimization to engineering system design”, PhD Thesis, Tese, Escola de Engenharia Mecânica, Universidade Federal de Uberlândia, Brasil, 2008.

[23]S. Y. Lim, M. Montakhab, e H. Nouri, “Economic dispatch of power system using particle swarm optimization with constriction factor”, *Int. J. Innov. Energy Syst. Power*, vol. 4, nº 2, 2009.

[24]Y. Sonmez, “Multi-objective environmental/economic dispatch solution with penalty factor using Artificial Bee Colony algorithm”, *Sci. Res. Essays*, vol. 6, nº 13, p. 2824–2831, 2011.

[25]J. de A. B. Júnior, M. V. A. Nunes, M. H. R. Nascimento, J. L. M. Rodríguez, e J. C. Leite, “Solution to economic emission load dispatch by simulated annealing: case study”, *Electr. Eng.*, vol. 100, nº 2, p. 749–761, 2018.

[26]M. H. R. Nascimento, M. V. A. Nunes, J. L. M. Rodríguez, e J. C. Leite, “A new solution to the economical load dispatch of power plants and optimization using differential evolution”, *Electr. Eng.*, vol. 99, nº 2, p. 561–571, 2017.

[27]M. Basu, “Economic environmental dispatch using multi-objective differential evolution”, *Appl. Soft Comput.*, vol. 11, nº 2, p. 2845–2853, 2011.

[28]A. A. El Ela, M. A. Abido, e S. R. Spea, “Differential evolution algorithm for emission constrained economic power dispatch problem”, *Electr. Power Syst. Res.*, vol. 80, nº 10, p. 1286–1292, 2010.

[29]L. H. Wu, Y. N. Wang, X. F. Yuan, e S. W. Zhou, “Environmental/economic power dispatch problem using multi-objective differential evolution algorithm”, *Electr. Power Syst. Res.*, vol. 80, nº 9, p. 1171–1181, 2010.

[30]M. A. Abido, “A niched Pareto genetic algorithm for multiobjective environmental/economic dispatch”, *Int. J. Electr. Power Energy Syst.*, vol. 25, nº 2, p. 97–105, 2003.

[31]M. A. Abido, “A novel multiobjective evolutionary algorithm for environmental/economic power dispatch”, *Electr. Power Syst. Res.*, vol. 65, nº 1, p. 71–81, 2003.

[32]M. A. Abido, “Environmental/economic power dispatch using multiobjective evolutionary algorithms”, *IEEE Trans. Power Syst.*, vol. 18, nº 4, p. 1529–1537, 2003.

[33]R. Arul, G. Ravi, e S. Velusami, “An improved harmony search algorithm to solve economic load dispatch problems with generator constraints”, *Electr. Eng.*, vol. 96, nº 1, p. 55–63, 2014.

[34]J. C. Leite, I. P. Abril, M. S. S. Azevedo, M. H. R. do Nascimento, N. M. Moraes, e A. M. Reis, “Multicriteria design of passive harmonic filters for industrial instalations using evolutionary computation

techniques”, *ITEGAM-JETIA J. Eng. Technol. Ind. Appl.*, vol. 1, nº 3, 2015.

[35] Q. Qin, S. Cheng, X. Chu, X. Lei, e Y. Shi, “Solving non-convex/non-smooth economic load dispatch problems via an enhanced particle swarm optimization”, *Appl. Soft Comput.*, vol. 59, p. 229–242, 2017.

[36] V. K. Kamboj, A. Bhadoria, e S. K. Bath, “Solution of non-convex economic load dispatch problem for small-scale power systems using ant lion optimizer”, *Neural Comput. Appl.*, vol. 28, nº 8, p. 2181–2192, 2017.

[37] J. de A. B. Júnior, M. H. R. Nascimento, C. A. O. de Freitas, J. C. Leite, e T. L. R. Carvajal, “Approach of economic-emission load dispatch using Ant Lion Optimizer”, *Int. J. Adv. Eng. Res. Sci.*, vol. 5, nº 7.

[38] N. M. Moraes, U. H. Bezerra, J. L. Moya Rodríguez, M. H. R. Nascimento, e J. C. Leite, “A new approach to economic-emission load dispatch using NSGA II. Case study”, *Int. Trans. Electr. Energy Syst.*, vol. 28, nº 11, p. e2626, 2018.

[39] M. Basu, “Dynamic economic emission dispatch using nondominated sorting genetic algorithm-II”, *Int. J. Electr. Power Energy Syst.*, vol. 30, nº 2, p. 140–149, 2008.

[40] M. Basu, “Fuel constrained economic emission dispatch using nondominated sorting genetic algorithm-II”, *Energy*, vol. 78, p. 649–664, 2014.

[41] A. A. El Ela, R. A. El-Sehiemy, A. M. Shaheen, e A. S. Shalaby, “Application of the crow search algorithm for economic environmental dispatch”, in *2017 Nineteenth International Middle East Power Systems Conference (MEPCON)*, 2017, p. 78–83.

[42] J. de A. B. Júnior, M. V. A. Nunes, M. H. R. Nascimento, C. A. O. de Freitas, J. C. Leite, e N. M. Moraes, “Ant Lion optimizer applied to economic emission load dispatch problems turning off the engines”, in *2018 13th IEEE International Conference on Industry Applications (INDUSCON)*, 2018, p. 829–836.

[43] S. Brini, H. H. Abdallah, e A. Ouali, “Economic dispatch for power system included wind and solar thermal energy”, *Leonardo J. Sci.*, vol. 14, nº 2009, p. 204–220, 2009.

[44] J. Zhu, *Optimization of power system operation*. John Wiley & Sons, 2015.

[45] V. Miranda e P. S. Hang, “Economic dispatch model with fuzzy wind constraints and attitudes of dispatchers”, *IEEE Trans. Power Syst.*, vol. 20, nº 4, p. 2143–2145, 2005.

[46] A. Dhamanda, A. Dutt, S. Prakash, e A. K. Bhardwaj, “A traditional approach to solve economic load dispatch problem of thermal generating unit using MATLAB programming”, *Int. J. Eng. Res. Technol. IJERT*, vol. 2, 2013.

[47] N. I. Nwulu e X. Xia, “Multi-objective dynamic economic emission dispatch of electric power generation integrated with game theory based demand response programs”, *Energy Convers. Manag.*, vol. 89, p. 963–974, 2015.

[48] L. Wang e C. Singh, “Environmental/economic power dispatch using a fuzzified multi-objective particle swarm optimization algorithm”, *Electr. Power Syst. Res.*, vol. 77, nº 12, p. 1654–1664, 2007.

[49] W.-T. Huang *et al.*, “Derivation and application of a new transmission loss formula for power system economic dispatch”, *Energies*, vol. 11, nº 2, p. 417, 2018.

[50] M. Gitizadeh e S. Ghavidel, “Improving transient stability with multi-objective allocation and parameter setting of SVC in a multi-machine power system”, *IETE J. Res.*, vol. 60, nº 1, p. 33–41, 2014.

[51] M. A. El-Shorbagy e A. A. Mousa, “Chaotic particle swarm optimization for imprecise combined economic and emission dispatch problem”, *Rev. Inf. Eng. Appl.*, vol. 4, nº 1, p. 20–35, 2017.

[52] S. Mirjalili, “The ant lion optimizer”, *Adv. Eng. Softw.*, vol. 83, p. 80–98, 2015.
[53] I. N. Trivedi, P. Jangir, e S. A. Parmar, “Optimal power flow with enhancement of voltage stability and reduction of power loss using ant-lion optimizer”, *Cogent Eng.*, vol. 3, nº 1, p. 1208942, 2016.
[54] S. Mirjalili, P. Jangir, e S. Saremi, “Multi-objective ant lion optimizer: a multi-objective optimization algorithm for solving engineering problems”, *Appl. Intell.*, vol. 46, nº 1, p. 79–95, 2017.
[55] L. C. Saikia e N. Sinha, “Automatic generation control of a multi-area system using ant lion optimizer algorithm based PID plus second order derivative controller”, *Int. J. Electr. Power Energy Syst.*, vol. 80, p. 52–63, 2016.
[56] T. H. Khoa, P. M. Vasant, M. S. Balbir Singh, e V. N. Dieu, “Solving economic dispatch problem with valve-point effects using swarm-based mean–variance mapping optimization (MVMOS)”, *Cogent Eng.*, vol. 2, nº 1, p. 1076983, 2015.
[57] S. Rajasomashekar e P. Aravindhababu, “Biogeography based optimization technique for best compromise solution of economic emission dispatch”, *Swarm Evol. Comput.*, vol. 7, p. 47–57, 2012.
[58] L. dos Santos Coelho e V. C. Mariani, “An efficient cultural self-organizing migrating strategy for economic dispatch optimization with valve-point effect”, *Energy Convers. Manag.*, vol. 51, nº 12, p. 2580–2587, 2010.
[59] “Previsão do tempo local, notícias e condições | Clima subterrâneo”. https://www.wunderground.com/?cm_ven=cgi (acessado mar. 24, 2020).