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A new metaheuristic method to solve the dynamic economic and emission dispatch problem while accounting for valve point effects

***Abstract**. Thermal power plants, vital for the production of electrical energy, pose challenges due to the emission of harmful gases, contributing to environmental pollution and global warming. To address these issues while ensuring cost-effective operation, the Dynamic Economic Emission Dispatch (DEED) was formulated. This paper addresses Dynamic Economic Emission Dispatch (DEED) problems incorporating varying real transmission losses and considering valve point effects, which make DEED a non-smooth and more complex optimization problem that requires an effective optimization method. The method proposed in this article is new metaheuristic method, inspired by the lifestyle of African vultures. The algorithm is called the African Vultures Optimization Algorithm (AVOA), it is first tested on 36 standard reference functions. (AVOA) was applied to standard 10, and 15 unit test systems to meet 24-hour load demands. Comparison of the obtained results with other research shows that the proposed method outperforms other methodologies in terms of reduction in fuel cost, emissions, and transmission losses.*

***Streszczenie.** Elektrownie cieplne, niezbędne do produkcji energii elektrycznej, stwarzają wyzwania ze względu na emisję szkodliwych gazów, przyczyniających się do zanieczyszczenia środowiska i globalnego ocieplenia. Aby rozwiązać te problemy, zapewniając jednocześnie opłacalną eksploatację, opracowano Dynamiczny Ekonomiczny Wysyłanie Emisji (DEED). W artykule omówiono problemy dynamicznego ekonomicznego wysyłania emisji (DEED), uwzględniając zmieniające się rzeczywiste straty w przekładni i uwzględniając efekty punktu zaworowego, które sprawiają, że DEED nie jest gładkim i bardziej złożonym problemem optymalizacyjnym, wymagającym skutecznej metody optymalizacji. Metoda zaproponowana w tym artykule jest nową metodą metaheurystyczną, inspirowaną stylem życia sępów afrykańskich. Algorytm nazywa się algorytmem optymalizacji sępów afrykańskich (AVOA) i jest najpierw testowany na 36 standardowych funkcjach odniesienia. (AVOA) zastosowano w standardowych 10 i 15 systemach testów jednostkowych, aby sprostać wymaganiom obciążenia 24-godzinnego. Porównanie uzyskanych wyników z innymi badaniami pokazuje, że proponowana metoda przewyższa inne metodyki pod względem redukcji kosztów paliwa, emisji i strat przesyłowych. (**Nowa metaheurystyczna metoda rozwiązywania dynamicznego problemu ekonomicznego i emisji przy uwzględnieniu efektu punktu zaworowego**)*

Keywords: dynamic economic emission dispatch, metaheuristic method, valve point effects, African Vultures Optimization Algorithm.
Słowa kluczowe: Dynamiczny Ekonomiczny Wysyłanie Emisji, metodą metaheurystyczną, efektów punktów zaworowych, algorytmem optymalizacji sępów afrykańskich.

Introduction

Thermal power plants generate electricity by burning fossil fuels such as coal, natural gas, or oil. The use of these facilities can have significant harmful effects on the environment and human health, producing substantial amounts of carbon dioxide (CO2) and other atmospheric pollutants. CO2 contributes to climate change by enhancing the greenhouse effect and accelerating global warming. Additionally, thermal power plants emit harmful atmospheric pollutants such as sulfur oxides (SOx) and nitrogen oxides (NOx), which can lead to acid rain, respiratory problems, and negative impacts on air quality. Fine particles released through the combustion of fossil fuels can also cause respiratory health issues, particularly affecting populations living in close proximity to thermal power plants, emphasizing the need to minimize these pollutant emissions [1].

In an electrical system, the Economic Dispatch (ED) problem focuses on optimizing the costs associated with energy production and distribution, ensuring that generated powers are optimally distributed to meet demand while minimizing production costs and transmission losses [2]. However, the optimal solution to the ED problem may no longer be satisfactory when environmental concerns are taken into account. When combined with the emissions from fossil fuel power plants, the problem becomes an Economic and Environmental Dispatch (EED). The goal of this problem is to minimize both multi-objective functions: fuel cost and gas emissions, while satisfying load demand and operational constraints.

Large thermal power plants have multiple steam admission valves. Each time an admission valve is opened, losses suddenly increase, causing ripples in the fuel cost curve. As the valve is opened, transmission losses gradually decrease until the valve is fully open. These effects, called Valve Point Effects (VPE), are used to control the unit's output power and reduce transmission losses [3].

Considering these effects, the (EED-VPE) problem can be classified as a nonlinear optimization problem with non-smooth and non-convex characteristics subject to various equality and inequality constraints. In the context of newer generations, such as forbidden zones [4] and ramp rate limits [5], which exhibit a high order of non-linearities, the (EED-VPE) problem becomes more complex, making it challenging to find globally optimal solutions. Academic attention has increasingly focused on Dynamic Economic Emission Dispatch (DEED) (over 24 hours), recognized as the optimal mode for real dispatching conditions. Efficient optimization algorithms are essential to optimally solve these problems.

Several studies have been published to address this problem. In [6], the author introduced a multi-objective optimization based on an enhanced flame optimization approach to locate the optimal solution of hybrid DEED, including renewable energy production. In [7], the authors improved the tunicate swarm method to explore the DEED search space, applied to systems with 5, 10, and 15 units. Authors in [8] suggested a multi-objective virus colony search algorithm (MOVCS) to solve the DEED problem in the electric system integrated with electric vehicles and wind turbines over a 24-hour period. Reference [9] presented a new multi-objective differential evolution algorithm to address DEED problem constraints. In [10], an enhanced exploratory optimization algorithm for whales

(EEWOA) was proposed to solve dynamic economic dispatch (DED), considering VPE and power loss constraints. Authors in reference [11] proposed an innovative equilibrium optimizer (EO) and a hybrid multi-objective approach combining differential evolution (DE), based on an optimization algorithm, to solve the dynamic economic emission dispatch (DEED) problem. The improved slimy mold algorithm (ISMA) developed in reference [12] is implemented to optimize economic emission dispatch (EED) problems, whether single or bi-objective, while considering VPE. In [13], authors addressed combined dynamic economic and environmental dispatch (DCEED) problems with variable real transmission losses, using four metaheuristic techniques: seagull optimization algorithm (SOA), crow search algorithm (CSA), tunicate swarm algorithm (TSA), and firefly algorithm (FFA). In [14], an enhanced particle swarm optimization algorithm (PSOCS) integrated with a clone selection principle (CS) from the artificial immune system is proposed to solve dynamic economic emission dispatch (DEED) problems.

This article proposes, presents, and applies a new, more efficient metaheuristic method called the African Vulture Optimization Algorithm (AVOA) [15] to solve the DEED problem, including VPE. Simulation results are implemented to indicate the robustness of AVOA. To demonstrate the effectiveness of the proposed approach, two test cases are discussed and compared with other algorithms from the literature.

Problem formulation of DEED

The DEED problem can be described as a nonlinear and dynamic mathematical optimization problem. DEED is a constrained optimization problem that attempts to simultaneously minimize cost and emissions, while satisfying equality and inequality constraints, including actual power balance and ramp rate bounds. The formulation of the DEED problem considers the following objectives and constraints.

Cost objective

The cost objective function, accounting for the valve-point effect, is formulated as the combined sum of a quadratic function and a sinusoidal function [3]:

(1) $\mathrm{F}(P_{i,t})=\sum_{i-1}^{N}(a_i\, P_{i,t}^2+b_iP_{i,t}+c_{i,t})+\,|d_i\sin(e_i(P_{i,min}\text{-}P_{i,t}))|$

Where $\mathrm{F}(P_i)$ is the total cost, a_i,b_i,c_i,d_i and e_i are the generator cost coefficients, $P_{i,t}$is the power generation and $P_{i,min}$ is the minimum power generation limits.

Emission objective

The function of the environmental dispatch problem is to reduce power plant gas emissions. It may be explained as follows

(2) $\mathrm{E}(P_{i,t})=\sum_{i-1}^{N}(\alpha_i\, P_{i,t}^2+\beta_iP_{i,t}+\gamma_i+\eta_i\exp(\delta_iP_{i,t}))$

Where $\mathrm{E}(P_{i,t})$ is the total emission, α_i,β_i,γ_i , η_i and δ_i are the emission coefficients.

Equality Constraints

To maintain power balance, it is necessary to satisfy an equality constraint. This constraint ensures that the total generated power equals the sum of the total load demand and the total line loss:

(3) $\sum_{i=1}^{nG}P_{i,t}= P_{D,t}+P_{L,t}$

Where $P_{D,t}$is the power demand and $P_{L,t}$ is the power loss. The expression of transmission loss as a function of the generated power is given by

(4) $P_{L,t}=\sum_{i=1}^{nG}\sum_{j=1}^{nG}P_{i,t}\,B_{ij}P_{j,t}+\sum_{i=1}^{nG}B_{0i}\,P_{i,t}+B_{0,0}$

Where B_{ij} , B_{0i} and $B_{0,0}$ are the constants called the losses coefficient.

Inequality Constraints

In accordance with this, all generating units must operate within a specified generation limit. Mathematically, this is expressed as:

(5) $P_{i,min}<P_{i,t}<P_{i,max}$

Where $P_{i,min}$ and $P_{i,max}$ are the minimum and maximum limits, respectivaly for the production the ith unit (in MW).

Rampe rate

In practical scenarios, the operational boundary for each generator is constrained by its ramp rate limit, meaning that the adjustment of the output power P_i cannot occur instantaneously. The limits for upward and downward ramps are denoted by:

(6) $\begin{cases}P_{i,t}-P_{i,t-1}-UR_i*\Delta T\le 0\\ P_{i,t-1}-P_{i,t}-DR_i*\Delta T\le 0\end{cases}$

Where UR_i and DR_i are the up and down limit of generator i, respectivaly. ΔT denotes the length of each dispatching time interval [14].

African vulture optimization algorithm

The new metaheuristic algorithm known as the African Vulture Optimization Algorithm (AVOA) was developed by Abdollahzadeh et al (2021)[15]. It is inspired by the way vultures hunt. This bird consumes dead animals and sometimes people. Although the carcasses can be infected and diseased. A brand new optimization algorithm called AVOA is used to mathematically model this behavior].

For the purpose of simulating the behavior of various vultures, the AVOA approach can be broken down into five parts [15].

Phase 1: Population Grouping

The suitability of all solutions is determined after training the initial population (starting with random initial individuals), using equation (7).

(7) $R(i)=\begin{cases}BestVulture_1\ if\ P_i=\ L_1\\ BestVulture_2\ \ if\ P_i=\ L_2\end{cases}$

Where, $BestVulture_1$ represents the best vulture and $BestVulture_2$ represents the second-best one, L1 and L2 describe two parameters in the interval [0, 1] that are achieved before optimization.and $L_1+L_2=1$.

Equation 8 is used to determine P_i , which was accomplished using the roulette technique[.

(8) $P_i=\frac{F_i}{\sum_{i=1}^{n}F_i}$

Phase 2: The Rate of Starvation of Vultures

TheF_i , a hunger level, of the ith vulture at the tth iteration is computed using Equation (9), which is employed as an indicator of the vultures shift from exploration to exploitation.This can be modeled as follows:

(9) $F_i=(2\ \times rand_i+1)\times z\times\left(1-\frac{iteration_i}{maxiterations}\right)+t$

Where F_i shows that the vultures have had enough, $rand_i$ is a variable whose random value is between 0 and 1, and z is a random value in the interval [1,1] that changes at each iteration, and t is calculated by equation (10)

(10) $$t = h \times \left(\begin{array}{c} \sin^{\omega}\left(\frac{\pi}{2} \times \frac{iteration_i}{maxiterations}\right) + \\ \cos^{\omega}\left(\frac{\pi}{2} \times \frac{iteration_i}{maxiterations}\right) - 1 \end{array} \right)$$

where, the probability of the vulture performing the exploitation step is determined by the parameter ω, which is specified in advance. In addition, h h is a random value between -2 and 2 .

Phase 3: Exploration stage

There are two different ways that AVOA vultures can inspect different random locations, and they can choose between them using the P1 parameter, which has a range of [0,1]. A random number between 0 and 1 called $rand_{P_1}$ is used to select one of the strategies during the exploration phase. If $rand_{P_1} > P_1$, equation (11) is used. In such a case, Otherwise equation (12) is applied.

(11) $$P(i+1) = R(i) - D(i) \times F_i$$

(12) $$P(i+1) = R(i) - F_i + rand_2 \times ((ub - lb) \times rand_3 + lb)$$

$R(i)$ is one of the best vultures selected in the current iteration using equation (6), $rand_2$ is a random number between 0 and 1, and lb and ub are the lower and upper bounds of the variables, respectively. $rand_3$ is utilized to give a high random coefficient throughout the search environment.

$D(i)$ is the distance between the vulture and the current optimum it is calculated according to equation 13

(13) $$D(i) = |X \times R(i) - P(i)|$$

Here, X is a random number between 0 and 2, and $P(i)$ is the position of the ith vulture.

Phase 4: Exploitation (First Stage)

If $F_i$has a value less than 1, the AVOA initiates the first operation phase. To choose which technique to adopt, utilize the parameter P_2 in the [0,1] range.If this $rand_{P_2}$ is greater than or equal to the parameterP_2, the siege-fight technique is employed slowly. The rotational flying technique is employed in all other cases. This process is shown in Equation (14).

(14)
$$P(i+1) = \begin{cases} D(i) \times (F_i + rand_4) - dt & if\ P_2 \geq rand_{P_2} \\ R(i) - (S_1 + S_2) & if\ P_2 \geq rand_{P_2} \end{cases}$$

where dt represents the distance between the vulture and one of the best vultures in the two groups, as determined by equation (15) , and $rand_4$is a random number between 0 and 1.

(15) $$d(i) = R(i) - P(i)$$

S_1 and S_2 are calculated using equations (16) and (17), respectively, as follows:

(16) $$S_1 = R(i) \times \left(\frac{rand_5 \times P(i)}{2\pi}\right) \times \cos(P(i))$$

(17) $$S_2 = R(i) \times \left(\frac{rand_6 \times P(i)}{2\pi}\right) \times \sin(P(i))$$

where, $rand_5$ and $rand_6$ are random numbers between 0 and 1, respectively

Phase 5: Exploitation (Second Stage)

the algorithm's following step is executed if $|F_i|$ is less than 0.5, the technique is used if the parameter P_3 is larger than or equal to $rand_3$. Equation (18) can therefore be used to update the vulture's location

(18) $$P(i+1) = \frac{A_1 + A_2}{2}$$

Equations (19) and (20) are used to calculate A_1 and A_2, respectively.

(19) $$A_1 = BestVulture_1(i) - \frac{BestVulture_1(i) \times P(i)}{BestVulture_1(i) \times (P(i))^2} \times F_i$$

(20) $$A_2 = BestVulture_1(i) - \frac{BestVulture_2(i) \times P(i)}{BestVulture_2(i) \times (P(i))^2} \times F_i$$

The position of the vultures be updated using equation (21)

(21) $$P(i+1) = R(i) - |d(t)| \times F_i \times levy(d)$$

Where, d represents the problem dimensions.

Equation (22) presents the derivation of the Lévy flight models (LF) used to increase the efficiency of the AVOA

(22) $$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma(1+2\beta) \times \beta \times \left(\frac{\beta-1}{2}\right)}\right)^{\frac{1}{\beta}}$$ (23) $$LF(x) = 0.001 \times \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}}$$

Results and discussion

AVOA is employed for addressing the DEED issue in two cases to guarantee optimal efficiency. In these papers, the objective function is characterized by multiple objectives constrained by the yield limits of production units and transport losses. The effectiveness of AVOA is assessed through a comparison with several optimization algorithms. To conduct this comparison, we have created programs within the MATLAB 7.9 environment.

Test case 1

In this case, we deal with combined dynamic economic and environmental dispatch (DEED) by considering power losses, valve point effect loading and ramp effects for a network of 10 units. The simulation results are in Table 1, which summarizes the best powers generated for 24 hours by varying the requested power which are presented in ref [14] with the network data. Table 2 presents a comparison of the results obtained with other methods such as (PSOCS) [14], (PSO) [16] and (DE-SQP) [17].

The results in Table 2 highlight that the suggested approach consistently achieved a lower total cost compared to the total costs derived from alternative algorithms.

Test case 2

This system is comprised of fifteen production units, each characterized by quadratic cost and emission functions that consider valve point effects and ramp effects. The input data utilized in the system is derived from [14], and the demand is varied over a 24-hour period to manage the network's operation for a day. The results from the proposed AVOA in this scenario are detailed in Table 3 and juxtaposed with outcomes from (PSOCS) [14], (PSOAWL) [16], and (PSO-SQP) [18] in Table 4, focusing on optimal economic and environmental conditions.

Table 2. Comparison of the 10-unit test system with previous algorithms for DEED

Algorithm	Total fuel cost ($) ($10^6$)	Total emission (lb) (10^5)
AVOA	2.493100	3.26510
PSOCS [14]	2.526900	2.980000
PSO [16]	2.604400	3.107500
DE-SQP [17]	2.46.88	3.1564

Table 4. Comparison of the 15-unit test system with previous algorithms for DEED.

Algorithm	Total fuel cost ($) ($10^6$)	Total emission (lb) (10^5)
AVOA	6.9431	3.0448
PSOCS [14]	7..0736	2.63625
PSOAWL [16]	7.06128	3.07726
PSO-SQP [18]	7.13682	3.02365

Table 1. Results of DEED (24 hours) for 10 Units.

T(h)	P1(MW)	P2(MW)	P3(MW)	P4(MW)	P5(MW)	P6(MW)	P7(MW)	P8(MW)	P9(MW)	P10(MW)	Pl(MW)
1	150.000	135.000	146.624	60.011	125.749	160.000	93.071	120.000	52.057	13.132	19.647
2	150.000	135.000	73.040	60.020	242.977	160.000	129.926	47.013	80.000	54.966	22.945
3	150.000	135.000	166.060	178.907	224.005	159.264	129.594	85.376	29.447	28.730	28.387
4	150.000	135.000	183.316	228.569	222.415	156.199	129.529	119.997	76.393	40.034	35.455
5	150.000	135.000	243.134	273.616	242.752	159.999	130.000	120.000	20.645	44.281	39.430
6	150.000	135.039	302.968	300.000	243.000	160.000	129.985	120.000	80.000	55.000	47.993
7	150.000	219.385	297.791	299.987	243.000	159.999	130.000	120.000	80.000	54.999	53.164
8	184.130	222.266	340.000	300.000	243.000	160.000	130.000	120.000	80.000	55.000	58.397
9	257.018	309.532	340.000	300.000	243.000	160.000	130.000	120.000	80.000	55.000	70.551
10	331.622	396.799	340.000	300.000	243.000	160.000	130.000	120.000	80.000	55.000	84.421
11	376.215	396.799	340.000	300.000	243.000	160.000	130.000	120.000	80.000	55.000	88.532
12	376.219	396.799	340.000	300.000	243.000	160.000	130.000	120.000	80.000	55.000	88.533
13	331.622	396.799	340.000	300.000	243.000	160.000	130.000	120.000	80.000	55.000	84.421
14	257.018	309.532	340.000	300.000	243.000	160.000	130.000	120.000	80.000	55.000	70.551
15	188.691	222.266	335.465	299.999	242.999	160.000	129.998	120.000	80.000	55.000	58.420
16	150.000	135.000	236.396	299.918	242.990	160.000	129.819	120.000	79.999	43.421	43.545
17	150.000	135.000	253.399	239.199	226.334	160.000	129.647	120.000	52.259	53.532	39.372
18	150.000	139.302	298.700	300.000	243.000	160.000	130.000	120.000	80.000	55.000	48.002
19	189.072	222.266	335.122	299.963	243.000	160.000	130.000	120.000	80.000	54.997	58.422
20	331.622	396.799	340.000	300.000	243.000	160.000	130.000	120.000	80.000	55.000	84.421
21	257.018	309.532	340.000	300.000	243.000	160.000	130.000	120.000	80.000	55.000	70.551
22	150.000	135.000	303.007	300.000	243.000	160.000	130.000	120.000	80.000	54.985	47.993
23	150.000	135.003	73.040	239.509	222.531	160.000	129.663	119.997	79.946	54.551	32.242
24	150.000	135.000	118.651	120.256	222.553	155.394	129.603	85.311	79.992	12.588	25.352

able 3. Results of DEED (24 hours) for 15 Units.

T	P1	P2	P3	P4	P5	P6	P7	P8
1	182.943	184.334	129.99	129.998	150.11	135.000	135.000	60.052
2	150.025	176.047	20.263	129.537	154.515	211.620	144.692	64.139
3	170.575	225.577	105.508	129.987	157.859	209.117	221.392	62.000
4	160.023	285.443	41.396	106.505	188.838	212.169	309.532	110.292
5	185.084	150.001	128.650	105.511	270.529	288.248	222.267	109.843
6	228.834	245.785	121.558	106.756	327.714	284.315	225.316	92.288
7	205.339	300.630	105.959	129.990	271.917	291.320	309.525	66.184
8	239.138	303.697	130.000	129.971	321.059	331.756	309.530	114.716
9	243.539	307.098	129.366	129.589	326.806	353.109	359.612	158.743
10	268.510	307.123	129.979	128.293	333.183	364.864	386.144	111.284
11	273.811	330.972	129.999	130.000	388.577	384.102	396.621	125.748
12	283.577	338.335	129.994	130.000	380.147	429.081	396.874	118.505
13	276.400	330.934	129.990	127.417	342.093	375.327	395.525	145.970
14	252.000	318.654	130.000	106.210	333.536	364.758	326.125	147.417
15	230.167	283.250	124.285	110.999	287.578	364.814	309.105	60.032
16	224.502	280.398	28.747	67.884	304.011	285.079	218.415	141.470
17	236.682	197.747	128.465	106.600	249.784	214.630	221.269	60.009
18	239.975	298.380	60.667	128.992	327.015	211.623	309.534	63.450
19	256.484	292.630	110.299	102.707	329.513	288.252	306.496	60.042
20	259.060	309.611	129.995	123.754	346.330	364.848	352.827	93.067
21	263.699	263.666	130.000	129.999	321.546	362.684	353.926	143.215
22	223.414	259.889	104.183	126.326	231.329	288.204	308.956	63.999
23	196.437	233.267	129.146	116.979	190.863	135.791	222.418	104.502
24	184.115	234.364	38.168	20.980	244.862	136.096	139.685	115.029

P9	P10	P11	P12	P13	P14	P15	Pl
25.154	25.941	20.021	20.013	25.000	15.000	15.000	82.578
85.366	74.860	20.032	80.000	25.003	15.025	15.000	112.129
26.386	83.480	20.033	56.505	29.717	15.000	15.002	113.137
85.424	36.438	46.349	56.819	63.331	25.518	15.000	162.082
83.629	74.263	72.947	58.118	63.063	33.126	15.023	196.308
80.024	75.201	79.998	56.557	63.317	36.047	48.411	243.127
32.648	159.992	79.992	59.234	63.323	51.470	18.410	236.946
84.738	30.253	80.000	25.734	85.000	51.127	15.159	259.883
87.996	64.060	79.993	68.70	74.837	53.891	43.133	328.481
84.928	159.270	80.000	79.977	85.000	54.847	48.421	367.827
151.571	123.984	80.000	79.998	84.997	50.477	49.060	435.923
157.763	108.209	80.000	79.999	84.999	54.999	48.424	426.912
145.832	74.839	80.000	80.000	84.478	54.071	48.421	387.301
79.978	124.597	62.609	79.945	67.073	54.969	48.421	344.299
81.634	94.482	79.974	47.807	70.392	47.056	48.411	247.992
37.603	127.327	40.502	78.836	63.385	46.470	48.418	248.053
141.790	25.074	42.413	68.650	63.214	47.054	48.426	187.814
88.509	81.478	77.546	61.427	63.329	29.150	15.000	227.081
131.256	124.730	48.415	75.289	63.511	48.334	48.420	294.385
143.865	135.730	49.886	79.985	84.998	51.366	48.412	369.740
34.127	152.078	80.000	80.000	82.575	47.118	27.092	323.730
25.000	74.864	70.611	79.999	63.312	47.048	48.420	187.561
30.427	73.391	41.754	58.084	68.660	15.050	48.418	159.193
85.890	25.000	20.001	79.993	63.404	47.060	48.423	146.075

Conclusion

The Dynamic Economic Emissions dispatch (DEED) problem presents a formidable challenge in optimization searches due to its non-smooth and non-convex characteristics, featuring multiple local optimal points that complicate the quest for the global optimum. In this study, we introduce a new innovative principle-based Improved Optimization Approach (AVOA) designed to address the intricacies of the DEED problem, considering loading effects at the valve point and the ramp rate. The fundamental idea behind this optimization technique is that metaheuristic algorithms are easy to implement and versatile for addressing various problems. Our experimental results, conducted on two test systems (10 and 15 unit systems), display the superior performance of the proposed algorithm compared to state-of-the-art methods documented in the existing literature.

REFERENCES

[1] Abdelhakem-Koridak, L., et al. "Optimisation du dispatching électrique et de l'émission des gaz par les algorithmes génétiques." Acta Electrotehnica 49 (2008): 194-199.

[2] Li, Xueping, Jian Xu, and Zhigang Lu. "Differential evolution algorithm based on state transition of specific individuals for economic dispatch problems with valve point effects." Journal of Electrical Engineering & Technology (2021): 1-14.

[3] Zhang, Yong, et al. "Hybrid bare-bones PSO for dynamic economic dispatch with valve-point effects." Applied Soft Computing 18 (2014): 248-260.

[4] Razali, N. S., et al. "Embedded immune-evolutionary programming for Economic Dispatch of generators with prohibited operating zones." (2018)..

[5] Vahidi, Mehdi, et al. "Evolutionary-base finite element model updating and damage detection using modal testing results." Structural Engineering and Mechanics, An Int'l Journal 70.3 (2019): 339-350.

[6] Liu, Zhi-Feng, et al. "Dynamic economic emission dispatch considering renewable energy generation: A novel multi-objective optimization approach." Energy 235 (2021): 121407.

[7] Li, L.-L.; Liu, Z.-F.; Tseng, M.-L.; Zheng, S.-J.; Lim, M.K. Improved tunicate swarm algorithm: Solving the dynamic economic emission dispatch problems. Appl. Soft Comput. 2021, 108, 107504.

[8] Zou, Yuwei, et al. "Solving dynamic economic and emission dispatch in power system integrated electric vehicle and wind turbine using multi-objective virus colony search algorithm." Sustainable Cities and Society 67 (2021): 102722.

[9] Li, Xueping, Jian Xu, and Zhigang Lu. "Differential evolution algorithm based on state transition of specific individuals for economic dispatch problems with valve point effects." Journal of Electrical Engineering & Technology (2021): 1-14.

[9] Qiao, Baihao, Jing Liu, and Xingxing Hao. "A multi-objective differential evolution algorithm and a constraint handling mechanism based on variables proportion for dynamic economic emission dispatch problems." Applied Soft Computing 108 (2021): 107419.

[10] Yang,W.; Peng, Z.; Yang, Z.; Guo, Y.; Chen, X. An enhanced exploratory whale optimization algorithm for dynamic economic dispatch. Energy Rep. 2021, 7, 7015–7029.

[11] Xia, Aiming, Xuedong Wu, and Yingjie Bai. "A new multi-objective hybrid optimization algorithm for wind-thermal dynamic economic emission power dispatch." International Transactions on Electrical Energy Systems 31.8 (2021): e12966.

[12] Hassan, Mohamed H., et al. "Development and application of slime mould algorithm for optimal economic emission dispatch." Expert Systems with Applications 182 (2021): 115205.

[13] Larouci, Benyekhlef, et al. "Investigation on New Metaheuristic Algorithms for Solving Dynamic Combined Economic Environmental Dispatch Problems." Sustainability 14.9 (2022): 5554.

[14] Qian, Shuqu, Huihong Wu, and Guofeng Xu. "Animproved particle swarm optimization with clone selection principle for dynamic economic emission dispatch." Soft Computing 24.20 (2020): 15249-15271.

[15] Ghazi, Ghazi A., et al. "African vulture optimization algorithm-based PI controllers for performance enhancement of hybrid renewable-energy systems." Sustainability 14.13 (2022): 8172.

[16] Mason, Karl, Jim Duggan, and Enda Howley. "Multi-objective dynamic economic emission dispatch using particle swarm optimisation variants." Neurocomputing 270 (2017): 188-197.

[17] Elaiw, A. M., X. Xia, and A. M. Shehata. "Hybrid DE-SQP and hybrid PSO-SQP methods for solving dynamic economic emission dispatch problem with valve-point effects." Electric Power Systems Research 103 (2013): 192-200.

[18] Elaiw, A. M., X. Xia, and A. M. Shehata. "Hybrid DE-SQP and hybrid PSO-SQP methods for solving dynamic economic emission dispatch problem with valve-point effects." Electric Power Systems Research 103 (2013): 192-200.