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ENHANCED LSHADESPACMA ALGORITHM FOR ENERGY HUB OPTIMIZATION INCORPORATING STOCHASTIC WIND AND SOLAR ENERGY

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Abstract

Nowadays, with the use of various energy technologies, interest in integrated energy systems is increasing, where the energy hub(EH) is the most attractive in them. EH optimization problems are the complex and high-dimensional due to the combining the different energy sources and the generation of different demands at the output. For this reason, the meta-heuristic search algorithms needs to be used to solve the EH problems. In this study, a novel LSHADE with semi-parameter adaptation hybrid with CMA-ES including fitness-distance balance(FDB-LSHADESPACMA) was developed to solve EH optimization problems. Using the five input energy carriers and four output energy sources, different EH structures were created and three test systems were presented to the literature for the first time. Besides, two objective functions were used which are minimization of total cost and total loss. To validate the performance of FDB-LSHADESPACMA, it was applied on benchmark and EH optimization problems. In experimental study about EH optimization problems, six case studies were considered. Accordingly, the FDB-LSHADESPACMA was obtained 3292.2784mu, 1.6753pu, 5052.0203mu, 2.1126pu, 5217.2151mu, and 2.7051pu for Case-1, Case-2, Case-3, Case-4, Case-5, and Case-6, respectively. The simulation results demonstrated that FDB-LSHADESPACMA achieved successful performance for solving both EH optimization and benchmark problems.

Keywords: Energy hub, Optimization, Fitness-Distance Balance, LSHADESPACMA algorithm

STOKASTİK RÜZGAR VE GÜNEŞ ENERJİSİNİN BİRLEŞTİRİLDİĞİ ENERJİ HUB OPTİMİZASYONU İÇİN GELİŞTİRİLMİŞ LSHADESPACMA ALGORİTMASI

Özet

Günümüzde çeşitli enerji teknolojilerinin kullanılmasıyla birlikte entegre enerji sistemlerine, özellikle enerji hub (EH) problemine olan ilgi artmaktadır. EH optimizasyon problemleri, farklı enerji kaynaklarının birleştirilmesi ve farklı taleplerin üretilmesi nedeniyle karmaşık ve yüksek boyutludur. Bu nedenle EH problemlerinin çözümü için meta-sezgisel arama algoritmalarının kullanılması gerekmektedir. Bu çalışmada, EH optimizasyon problemlerini çözmek için FDB-LSHADESPACMA olarak isimlendirilen uygunluk-mesafe dengesi tabanlı yarı parametre uyarlamalı LSHADE ile hibrit CMA-ES (LSHADE-SPACMA) algoritması önerilmiştir. Çalışmada, beş giriş enerji taşıyıcısı ve dört çıkış enerji kaynağı kullanılarak farklı EH yapıları oluşturulmuş ve üç test sistemi ilk kez literatüre sunulmuştur. Ayrıca, toplam maliyetin ve toplam kaybın minimizasyonu olmak üzere iki amaç fonksiyonu kullanılmıştır. Önerilen algoritmanın performansı, kıyaslama ve EH optimizasyon problemleri üzerinde test edilmiştir. EH optimizasyon problemlerine yönelik deneysel çalışmada altı durum çalışması dikkate alınmıştır. Buna göre, FDB-LSHADESPACMA Durum-1, Durum-2, Durum-3, Durum-4, Durum-5 ve Durum-6 için sırasıyla 3292.2784mu, 1.6753pu, 5052.0203mu, 2.1126pu, 5217.2151mu ve 2.7051pu değerlerini elde etti. Simülasyon sonuçları, FDB-LSHADESPACMA algoritmasının hem EH optimizasyonu hem de kıyaslama problemlerinin çözümünde üstün performans elde ettiğini göstermiştir.

Anahtar Kelimeler: Enerji hub, Optimizasyon, Uygunluk-Mesafe Dengesi, LSHADESPACMA algoritması

Cite

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1. Introduction

Energy has always been one of the people's most important and basic requirements from past to the present. The need for energy has become increasingly significant as a result of increasing population, finite fossil fuel resources, ever-increasing energy consumption, human life's increasing dependence on energy, and the emergence of various energy consumer technologies [1-3]. Fossil fuels are the primary source of energy for power plants. However, the depletion of fossil fuel sources and their environmental effects have prompted consideration of alternative energy sources [2, 3]. Furthermore, traditional energy systems have been operated and planned independently. On the other hand, residential, commercial, and industrial customers need different types of energy. For these reasons, the utilization of integrated energy systems has grown unavoidable in recent years, as new technologies have emerged. Nonetheless, the interactions between various energy systems have greatly expanded [4, 5]. Different energy infrastructures, such as electricity, natural gas, and heat, can operate together in the multi-energy systems unlike the conventional system. As a result, the energy hub (EH) concept has been arisen to provide the optimal operation of multi-energy systems (MESs).

EH can be defined as an interface between energy producers and consumers, where the multiple energy carriers (MECs) are used to meet various types of demands. Various different EH structures have been introduced in the literature. Generally, the inputs can be electricity, heat, and natural gas among them. The energy conversion between different energy forms can be done via transformers, combined heat and power (CHP) technologies, heater exchangers, and other devices. The outputs of the EH can be electricity, heat, and cooling [6, 7].

In the literature, several studies have been carried out about energy hub optimization problems. In studies on this subject, generally, the total energy cost of the EH was to minimize. The authors in [6] proposed an EH model to solve the optimal power flow (OPF) problem. The goal of the problem was to minimize the total production costs. The same authors introduced an EH model with MECs, where an optimization approach for the optimal power dispatch problem was developed in [8]. In another study, the same authors introduced a steady-state power flow model involving the conversion and transmission of any number of energy carriers for the optimization of combined power [7]. In [9], the authors developed a method for decomposing the combined power flow studies using MECs into the traditional OPF problem.

In addition to electricity, heat, and natural gas energy sources, renewable energy sources have been used in the EH. In [10], the optimal management strategy of electrical and thermal resources in a micro-grid with EH was presented. The objective of the proposed model was to minimize the expected operation costs while considering all network constraints and uncertainties. In [11], an EH model integrated wind and solar energy was proposed. The objective was to minimize the total operation cost of the system and a mixed-integer linear programing formulation for this problem was proposed. The authors in [12] proposed a smart EH system. The aim was to minimize the operation cost, the deviation of the electrical load profile from its desired value, and the emission pollution.

In the literature, to solve the operation cost of the EH system, the researchers were used to meta-heuristic search (MHS) algorithms. The authors presented the modified TLBO algorithm to decrease the cost of the system. In [13], the authors presented an algorithm called TVAC-PSO and applied it on MECs economic dispatch problems. In [14], the same groups proposed a novel algorithm called SAL-TVAC-GSA to solve the EH optimization problems. Three objective functions, which were the minimization of total cost, the minimization of total loss, and the minimization of total cost and loss, simultaneously. The authors in [15] proposed Fitness-Distance Balance (FDB) based LSHADE algorithm in order to solve the EH optimization problems. The results of the problems showed that the proposed algorithm was a competitive performance compared to its competitors.

In this study, an EH model integrated with wind and solar energy was proposed, where the inputs of the EH were wind energy, natural gas, electricity, solar energy, and heat, and the demands of it were electricity, cooling, heat, and compressed air. Based on this model, sixteen EH structures were presented and by using them, three different scale test systems were created. Besides, two objective functions were considered: minimization of the total EH cost and minimization of the total EH losses. Using these test systems and two objective functions, six case studies were carried out. The other most important point of the study was that FDB based LSHADESPACMA algorithm was proposed to solve the EH optimization problems. In order to compare the performance of the proposed algorithm in solving EH optimization problems, 14 MHS algorithms were considered. The performance of the algorithms was compared according to the best optimal solution values obtained from them and the statistical analysis methods. The contributions of the article to the literature can be summarized as below:

- Novel EH test systems were introduced to the literature.
- The FDB-LSHADESPACMA algorithm was presented to the literature as a strong MHS algorithm.
- A comprehensive simulation studies were presented to the literature in both the solution of the benchmark and EH optimization problems.

- The statistical analysis were carried out to prove the performance of the proposed algorithm.

The remainder of this paper is organized as follows: Section 2 defines proposed EH structures, the formulation of the objective functions and the constraints of the problem, and the stochastic modelling of wind and solar energy sources. Section 3 introduces the proposed FDB-LSHADESPACMA algorithm. In section 4, all results of the simulation studies carried out on the solving both EH optimization and benchmark problems are presented and analyzed. Section 5 summarizes the conclusions.

2. Formulation of the Energy Hub Optimization Problem

2.1. Energy Hub structures

In the literature, different definitions of EH have been presented by the researchers. EH receives various energy carriers and produces the desired demands at the output ports. Because the input and output ports on EH might vary, a multiple input and multiple output energy hub system is modeled as follows [6]:

$$\underbrace{\begin{bmatrix} E_\delta^{out} \\ E_\beta^{out} \\ \vdots \\ E_\omega^{out} \end{bmatrix}}_{E_{out}} = \underbrace{\begin{bmatrix} C_{\delta\delta} & C_{\delta\beta} & \cdots & C_{\delta\omega} \\ C_{\beta\delta} & C_{\beta\beta} & \cdots & C_{\beta\omega} \\ \vdots & \vdots & \ddots & \vdots \\ C_{\omega\delta} & C_{\omega\alpha} & \cdots & C_{\omega\omega} \end{bmatrix}}_{C} \underbrace{\begin{bmatrix} E_\delta^{in} \\ E_\beta^{in} \\ \vdots \\ E_\omega^{in} \end{bmatrix}}_{E_{in}} \tag{1}$$

where E_{out} and E_{in} are the output and input energy vector, respectively, the subscripts $\{\delta,\beta,\ldots,\omega\}$ represent the energy carriers, and C is the coupling matrix.

The general structure of EH used in this study is given in Figure 1. In the structure, there are five input energy carriers, including wind energy (w), electricity (e), natural gas (g), solar energy (s), and heat (h), and four output energy carriers including electricity (e), compressed air (a), heat (h), and cooling (c). In addition, there are two dispatch factors: v_1 is used for output and v_2 is used for input.

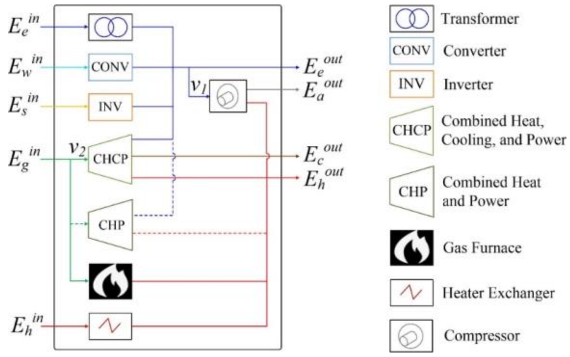

Figure 1. The model of the EH structure.

The EH structures proposed in this study are presented in the Table 1. The mathematical expressions of the EH structures can be obtained using Equation (1) and the data in Table 1.

Table 1. EH structures proposed in this study [37]

Hub No	Inputs						Energy Conversion Elements							Outputs			
	e	w	s	g	h	T	CONV	INV	CHP	CHCP	GF	C	HE	e	h	c	a
1	•					▪								✓			
2		•		•			▪			▪	▪			✓	✓		✓
3			•	•				▪	▪	▪		▪		✓	✓	✓	✓
4	•		•	•		•		▪			▪			✓	✓		
5	•			•		•			▪		▪	▪		✓	✓		✓
6		•		•			▪			▪	▪	▪		✓	✓	✓	✓
7	•	•		•		▪	▪			▪		▪		✓	✓	✓	✓
8		•	•	•	•		▪	▪	▪				▪	✓	✓		
9			•	•	•			▪		▪	▪	▪	▪	✓	✓	✓	✓
10	•		•	•		▪		▪		▪	▪	▪		✓	✓	✓	✓
11		•	•	•	•		▪	▪	▪	▪	▪		▪	✓	✓		
12		•	•	•	•		▪	▪		▪	▪	▪	▪	✓	✓		✓
13	•	•	•	•		▪	▪	▪	▪		▪			✓	✓		
14	•	•	•	•		▪	▪	▪		▪		▪		✓	✓	✓	✓
15	•	•		•	•	▪	▪		▪		▪	▪	▪	✓	✓		✓
16	•	•	•	•		▪	▪	▪		▪	▪	▪		✓	✓	✓	✓

2.2. Mathematical modeling of the energy hub optimization problems

The EH systems involves five input energy sources (i.e., wind energy, natural gas, electricity, solar energy, and heat). The cost models of them are evaluated separately as below.

2.2.1. Cost model of electrical energy carrier

Conventionally, the cost model of thermal generating units is calculated as [14, 15]:

$$C_{e0} = \sum_{i=1}^{N}\left(x_{i,e} + y_{i,e}P_{i,e} + z_{i,e}\left(E_{i,e}\right)^2\right) \tag{2}$$

where $x_{i,e}, y_{i,e}, z_{i,e}$ denote the cost coefficients for thermal generating unit, N is the total number of generating units, and $E_{i,e}$ is the output power of i^{th} generating unit. The total cost including valve-point loading effect (VPLE) is defined as [14, 15]:

$$C_e = \sum_{i=1}^{N_e} \left(\begin{aligned} & x_{i,e} + y_{i,e}E_{i,e}^{in} + z_{i,e}\left(E_{i,e}^{in}\right)^2 + \\ & \left| \sigma_{i,e} \sin\left(\xi_{i,e}\left(E_{i,e}^{in,\min} - E_{,,e}^{in}\right)\right) \right| \end{aligned} \right) \tag{3}$$

where $\sigma_{i,e}$ and $\xi_{i,e}$ are the cost coefficients of the VPLE for the i^{th} electrical carrier. C_e represents the total cost of the electrical energy carrier and $E_{i,e}^{in,\min}$ is the minimum value of energy production of i^{th} source, respectively. N_e is the number of electrical energy carriers.

2.2.2. Cost model of heat and natural gas energy carriers

The costs of heat and natural gas energy carriers can be modelled based on the cost model of classical thermal generation units given in Equation (2) [14, 15]. The cost models of heat and natural gas energy carriers are expressed by Equations (4) and (5), respectively. Here, CF_h and CF_g are the total energy cost of the heat and natural gas, respectively. $E_{j,h}^{in}$ and $E_{k,g}^{in}$ are the energy production of j^{th} heat carrier and the energy production of k^{th} natural gas carrier, respectively. N_h and N_g are the number of the heat and natural gas energy carriers.

$$C_g = \sum_{k=1}^{N_g} \left(x_{k,g} + y_{k,g}E_{k,g}^{in} + z_{k,g}\left(E_{k,g}^{in}\right)^2 \right) \tag{4}$$

$$C_h = \sum_{j=1}^{N_h} \left(x_{j,h} + y_{j,h}E_{j,h}^{in} + x_{j,h}\left(E_{j,h}^{in}\right)^2 \right) \tag{5}$$

2.2.3. Cost model of wind energy

Three components make up the overall cost of wind energy: the reserve cost for the overestimation, the penalty cost for the underestimation, and the direct cost related to the planned electricity. The total cost of the wind power plant is denoted as [16, 17]:

$$CF_w = \sum_{j=1}^{N_{wg}} \left[\begin{aligned} & C_{Pw,j}\left(P_{wav,j} - P_{ws,j}\right) + C_{w,j}\left(P_{ws,j}\right) + \\ & C_{Rw,j}\left(P_{ws,j} - P_{wav,j}\right) \end{aligned} \right] \tag{6}$$

Where $C_{Pw,j}\left(P_{wav,j} - P_{ws,j}\right)$, $C_{Rw,j}\left(P_{ws,j} - P_{wav,j}\right)$, and $C_{w,j}\left(P_{ws,j}\right)$ are the penalty cost, the reserve cost, and direct cost for the wind power plant, respectively, and N_{wg} is the number of wind generators. To obtain more information about the cost model of the wind power plant, you can review the ref. [16].

2.2.4. Cost model of solar energy

Similar to wind energy explained above, the total cost of solar energy is comprised of three costs: direct, penalty, and reserve. The solar power plant's overall cost is stated as [16, 17]:

$$CF_s = \sum_{j=1}^{N_{sg}} \left[\begin{aligned} & C_{Rs,k}\left(P_{ss,k} - P_{sav,k}\right) + C_{s,k}\left(P_{ss,k}\right) + \\ & C_{Ps,k}\left(P_{sav,k} - P_{ss,k}\right) \end{aligned} \right] \tag{7}$$

where $C_{Ps,k}\left(P_{sav,k} - P_{ss,k}\right)$, $C_{Rs,k}\left(P_{ss,k} - P_{sav,k}\right)$, and $C_{s,k}\left(P_{ss,k}\right)$ are the penalty cost, the reserve cost, and the direct cost for the solar power plant, respectively, and N_{SG} is the number of solar generators. To obtain more information about the cost model of the solar energy, you can review the ref. [16].

2.2.5. Objective functions

In this study, three objective functions are evaluated.

(i) Minimization of total EH cost: The cost function includes the cost of the input energy carriers. The sum of them gives the total cost of the system given in Equation (8).

$$OF_1 == \sum_{m=1}^{N_{hub}} \left(CF_{e,m} + CF_{g,m} + CF_{h,m} + CF_{w,m} + CF_{s,m} \right) \tag{8}$$

Here, N_{hub} represents the total number of EH structures and OF_1 stands for the objective function.

(ii) Minimization of total EH loss: The objective function related to the minimization of EH loss is expressed as below:

$$OF_2 = \sum_{\substack{p \in \{e,w,s,g,h,\} \\ n \in \{e,a,h,c\}}} \sum_{m=1}^{N_{hub}} \left(E_{m,p}^{in} - E_{m,n}^{out} \right) \tag{9}$$

where OF_2 refers to objective function and $E_{m,n}^{out}$ stands for the output energy of the systems.

2.2.6. Constraints

Equality constraint includes the balance between the produced energy and the demands of the system. This constraint can be expressed as:

$$\sum_{m=1}^{N_{hub}} E_{m,n}^{out} = E_n^{demand}, \quad n \in \{e,h,a,c\} \tag{10}$$

Inequality constraints include the operational limits and limits of the dispatch factor values of the EH structure.

(*i*) *Operational limits of EH unit*:

$$E_{j,i}^{in,min} \le E_{j,i}^{in} \le E_{j,i}^{in,max}, \quad i \in \{e,w,s,g,h\} \text{ and } j = 1,\ldots,n_i \tag{11}$$

(*ii*) *Limitation of dispatch factor of EH*:

$$0 \le v_1 \le 1, \ 0 \le v_2 \le 1 \tag{12}$$

2.2.7. Stochastic modeling of wind and solar energy

Generally, Weibull Probability Density Function (PDF) is used to determine the wind speed distribution [16, 17]. The Weibull PDF is given in Equation (13), where k_w and c_w represent shape and scale parameters for the PDF, respectively, and v is the probability of wind speed. The mean value of the Weibull PDF is defined as:

$$f_v(v) = \left(\frac{k_w}{c_w}\right)\left(\frac{v}{c_w}\right)^{k_w - 1} e^{-\left(v/c_w\right)^{k_w}}, \quad 0 < v < \infty \tag{13}$$

The output power of the solar energy systems is associated with solar irradiance (G). Lognormal PDF correctly defines the distribution of solar irradiance [16, 17]. The Lognormal PDF is given in Equation (14), where

σ and μ are standard deviation and mean values of the Lognormal PDF, respectively.

$$f_G(G)=\frac{1}{G*\sigma\sqrt{2\pi}}exp\left\{\frac{-(ln\,x-\mu)^2}{2\sigma^2}\right\},\quad G>0 \tag{14}$$

In this study, the solar and wind energy PDF parameters were obtained from [16]. Besides, you can check the reference [16] to learn more about the stochastic modeling of the wind and solar energy sources.

3. Proposed FDB-LSHADESPACMA Algorithm

In this study, the LSHADESPACMA algorithm was enhanced by using the Fitness-Distance Balance (FDB) [18] method and the proposed algorithm was named as FDB-LSHADESPACMA. The LSHADESPACMA algorithm, which is a population-based MHS algorithm, is an advanced variant of the DE algorithm [19]. The DE algorithm simulates the evolution process of the population in nature by using mutation, crossover, and selection operators in the optimization process. Generally, it has good global exploration capability to find the global optimum solution; however, it is slow in the neighborhood search of the solution [20, 21]. Therefore, the researchers have suggested different strategies to enhance the DE algorithm. The crossover operator and the mutation strategy are greatly affected the performance of the DE. In the literature, the new mutation strategies have been developed and the different versions of DE algorithm have been proposed.

In this study, the mutation strategy of the algorithm was redesigned using the FDB selection method. Accordingly, four different variations or cases of FDB based LSHADESPACMA have been created. The definitions and mathematical models of the FDB-LSHADESPACMA variations (Case-1, Case-2, Case-3, Case-4) created using the FDB selection method are given in Table 2. Table 2 provides the information about the proposed FDB-LSHADESPACMA variants. Accordingly, the mutation strategy “DE/current-to-pbest/1/bin” was used to create the mutant vector in Case-1. In Equation (15), the candidate selected by the FDB method x^G_{FDB} is used instead of the x^G_{r1} solution candidate. In Case-2, the mutation strategy used in the original LSHADESPACMA algorithm was changed and the “DE/current-to-rand/1/bin” mutation strategy (Mohamed et al., 2019) was used. Here, as in Case-1, the solution candidate was selected by FDB method, x^G_{FDB}, is used instead of the x^G_{r1} solution candidate. Case-3 is similar to Case-1; however, instead of the x^G_{r1} solution candidate, the candidate was selected by the Roulette FDB method x^G_{RFDB} is used. In Case-4, it has the same structure as Case-2, and the candidate solution was selected by Roulette FDB x^G_{RFDB} is used instead of the x^G_{r1} candidate solution. The FDB-based LSHADESPACMA variants were created to enhance the balanced search capability and the exploration ability of the LSHADESPACMA algorithm.

Table 2. Mathematical model of the FDB-LSHADESPACMA algorithm [37]

	Explanation	Mathematical Model of FDB-LSHADESPACMA Variations	
Case-1	Here, “DE/current-to-pbest/1/bin strategy” was used as the mutation strategy. The solution candidate was chosen by the FDB method $\left(x^G_{FDB}\right)$ was substituted for $x^G_{r_1}$.	$v_i^G=x_i^G+F_i^G.\left(x^G_{pbest}-x_i^G\right)+F_i^G.\left(x^G_{FDB}-x^G_{r_2}\right)$	(15)
Case-2	Here, “DE/current-to-rand/1/bin” strategy was used as the mutation strategy. The solution candidate was chosen by the FDB method $\left(x^G_{FDB}\right)$ was substituted for $x^G_{r_1}$.	$v_i^G=x_i^G+F_i^G.\left(x^G_{FDB}-x_i^G\right)+F_i^G.\left(x^G_{r_2}-x^G_{r_3}\right)$	(16)
Case-3	Here, “DE/current-to-pbest/1/bin strategy” was used as the mutation strategy. The solution candidate was chosen by the roulette wheel FDB method $\left(x^G_{RFDB}\right)$ was substituted for $x^G_{r_1}$.	$v_i^G=x_i^G+F_i^G.\left(x^G_{pbest}-x_i^G\right)+F_i^G.\left(x^G_{RFDB}-x^G_{r_2}\right)$	(17)
Case-4	Here, “DE/current-to-rand/1/bin” strategy was used as the mutation strategy. The candidate chosen by the roulette wheel FDB method $\left(x^G_{RFDB}\right)$ was substituted for $x^G_{r_1}$.	$v_i^G=x_i^G+F_i^G.\left(x^G_{RFDB}-x_i^G\right)+F_i^G.\left(x^G_{r_2}-x^G_{r_3}\right)$	(18)

4. Simulation Study and Results

The accuracy and analysis data derived from simulation studies is a key concern, since MHS algorithms are non-deterministic approaches. As a result, while testing and comparing the MHS algorithms, the equity and standard compliance are critical. As a result, the maximum number of fitness evaluations (*maxFEs*) was utilized as the termination condition for all algorithms, with the value set to 10000*Dimension. Furthermore, the CEC2017 and CEC2020 benchmark test suites were employed to validate the algorithms' performance. There are 39 problems in all over two benchmark suites. The experiments were conducted in 30-, 50-, and 100-dimensional search spaces for each challenge. There were 51 independent trials for each difficulty.

To affirm the performance of the FDB-LSHADESPACMA algorithm, it was compared with the 14-competing MHS algorithms, including marine predators algorithm (MPA) [22], equilibrium optimizer (EO) [23], barnacle mating optimizer (BMO) [24], artificial electric field algorithm (AEFA) [25], adaptive guided differential evolution algorithm (AGDE) [28], supply-demand-based optimization (SDO) [27], artificial ecosystem-based optimization (AEO) [26], coyote optimization algorithm (COA) [29], salp swarm algorithm (SSA) [30], LSHADE-SPACMA, linear population size reduction success history based adaptive DE (LSHADE) [32], moth flame optimization (MFO) [31], gravitational search algorithm (GSA) [33], and genetic algorithm (GA) [34]. When specifying the parameters of the algorithms, the data in the articles was used as a reference. To establish a fair comparison, the parameters of the proposed FDB-LSHADESPACMA algorithm were set to the same values as the base LSHADESPACMA algorithm.

4.1. Determining the best FDB-LSHADESPACMA method on benchmark test suites

In this section, the search performances of the LSHADESPACMA and its variations were presented. To evaluate and test the performance of four different variants and the LSHADESPACMA algorithm, six experiments were carried out. Three dimensions (30/50/100) and two benchmark suites (CEC2017 [35] and CEC2020 [36]) were used in these experiments. In the Friedman tests, the error values of the algorithms in each experiments were used. The Friedman test results of the LSHADESPACMA and its variations are listed in Table 3. The highest score for each experiment is highlighted in bold in Table 3.

Table 3. Friedman test results of the LSHADESPACMA and its variations [37]

	Case-1	Case-2	Case-3	Case-4	LSHADE SPACMA
CEC2017(D =30)	2.6528	3.3465	**2.3891**	3.167	3.4446
CEC2020(D =30)	2.8137	3.101	**2.5549**	3.0431	3.4873
CEC2017(D =50)	2.4804	3.4385	**2.2657**	3.4493	3.3661
CEC2020(D =50)	2.6833	3.3392	**2.2314**	3.1314	3.6147
CEC2017(D =100)	2.6085	3.6464	**2.0801**	3.4459	3.2191
CEC2020(D =100)	2.6882	3.5922	**1.8324**	3.3627	3.5245
Mean Rank	2.6545	3.4106	**2.2256**	3.2666	3.4427

Besides Friedman test, the Wilcoxon signed-rank test was applied. The Wilcoxon test was used to compare the base LSHADESPACMA algorithm with each variant. Table 4 shows the analysis findings from 24 separate comparisons.

Table 4. Wilcoxon test results between LSHADESPACMA and its variations [37]

vs.	*D* = 30		*D* = 50		*D* = 100	
LSHADE SPACMA +/=/-	CEC 2017	CEC 2020	CEC 2017	CEC 2020	CEC 2017	CEC 2020
Case-1	22/7/0	5/5/0	21/8/0	7/3/0	22/7/0	9/1/0
Case-2	10/17/2	4/6/0	11/10/8	5/4/1	8/9/12	3/5/2
Case-3	23/6/0	8/2/0	26/3/0	8/2/0	25/4/0	10/0/0
Case-4	12/16/1	4/6/0	10/10/9	5/4/1	9/7/13	5/2/3

According to Table 4, for *D*=30, it was seen that all FDB-LSHADESPACMA variations outperformed the base algorithm in both CEC2017 and CEC2020 benchmark test suites. Case-3 yielded the best results in these experiments compared to other variations, with scores for CEC2017 test problems (23/6/0) and CEC2020 test problems (8/2/0), surpassing the base algorithm in 31 of 39 test problems in total and showed 8 similar results.

According to the analysis results, Case-3 was the most effective LSHADESPACMA variation of them all. In the following sections, the Case-3 version is referred to as the FDB-LSHADESPACMA.

4.2. Application of the proposed FDB-LSHADESPACMA algorithm for solving the energy hub optimization problems

In this section, the FDB-LSHADESPACMA and other 14 MHS algorithms were applied to solve the EH optimization problems given in Section 2.2.5. Within the framework of EH optimization, three test systems were created using the EH structures proposed in Section 2. Accordingly, the proposed EH test systems are presented in Table 5. The minimum, mean, standard deviation, and maximum fitness values obtained as a result of 30 independent runs from the algorithms are given in Table 9.

Table 5. The proposed EH test systems [37]

Test Systems	Energy Hubs	*D*	Demand Values (pu)			
			e	h	c	a
Test System-1	1, 2, 10, 11, 16	20	3.5	3.5	0.5	0.9
Test System-2	1, 5, 7, 9, 12, 13	24	5	4.5	0.6	1
Test System-3	1, 3, 4, 6, 8, 14, 15	26	6	5	1	1.5

4.2.1. Results of the Test System-1

The information of the Test System-1 was given in Table 5. Here, two case studies were considered. The optimal solutions of the Test System-1 for Case-1 and Case-2 obtained by proposed algorithm are given in Table 6.

Table 6. The optimal solutions for Case-1 and Case-2 obtained by proposed algorithm [37]

Hub No	Input Energy	Case-1	Case-2
1	Electricity	0.7499	0.5085
2	Wind	0.3447	0.1549
	Gas	0.9403	0.1000
10	Electricity	0.1000	0.1963
	Solar	0.3656	0.1000
	Gas	1.8944	1.4612
11	Wind	0.2373	0.7482
	Solar	0.4998	0.4997
	Gas	1.8443	1.7946
	Heat	0.3142	0.2086
16	Electricity	1.1517	1.5000
	Wind	0.3409	0.6000
	Solar	0.1000	0.1000
	Gas	1.1747	1.7036
Total Cost (mu)		**3292.2784**	3653.9692
Total Loss (pu)		2.0577	**1.6753**

Case-1: Minimization of total energy hub cost

In this case, the minimization of total EH cost was the objective function given in the Equation (8). Accordingly, the obtained total cost by the FDB-LSHADESPACMA was 3292.2784 mu; this was the minimum value compared to the other algorithms where the total EH cost values obtained by the MPA, BMO, AEFA, EO, AEO, SDO, AGDE, COA, SSA, LSHADESPACMA, MFO, LSHADE, GSA, and GA algorithms were 3460.9732 mu, 3321.6194 mu, 3459.0479 mu, 3437.4563 mu, 3493.1946 mu, 3449.0242 mu, 3330.6835 mu, 3340.7766 mu, 3557.2218 mu, 3337.8356 mu, 3393.1189 mu, 3336.5610 mu, 3524.4668 mu, and 3471.8640 mu. When comparing the mean total cost value of all algorithms presented in Table 9, the obtained result from the FDB-LSHADESPACMA algorithm was the minimum value with 3343.1827 mu.

Case-2*: *Minimization of energy hub loss

The objective function in this case was to minimize the total EH loss given in the Equation (9). According to the results of all algorithms presented in Table 9, the lowest loss value was obtained from the FDB-LSHADESPACMA (1.6753 pu) algorithm than the MPA (1.9205 pu), EO (1.7547 pu), BMO (1.6895 pu), AEFA (1.7077 pu), AEO (1.8753 pu), SDO (1.8602 pu), AGDE (1.8236 pu), COA (1.7155 pu), SSA (1.8214 pu), LSHADESPACMA (1.6833 pu), MFO (1.6864 pu), LSHADE (1.8756 pu), GSA (1.8648 pu), and GA (1.8227 pu) algorithms. Meanwhile, from Table 9, the FDB-LSHADESPACMA algorithm yielded the best mean value (1.6753 pu) among all algorithms.

4.2.2. Results of the Test System-2

This test system includes the 6 EH structures and all information about the test system is given in in Table 5. Using this test system, two case studies were considered. The optimal solutions of the Case-3 and Case-4 obtained by proposed algorithm are listed in Table 7.

Table 7. The optimal solutions for Case-3 and Case-4 obtained by proposed algorithm [37]

Hub No	Input Energy	Case-3	Case-4
1	Electricity	0.1001	0.6265
5	Electricity	1.8952	1.6557
	Gas	1.1475	1.3572
7	Electricity	1.2492	1.5183
	Wind	0.1741	0.4835
	Gas	2.4432	2.6666
9	Solar	0.1435	0.2699
	Gas	0.9985	0.6560
	Heat	0.5682	1.3430
12	Wind	0.3742	0.3819
	Solar	0.4996	0.3192
	Gas	0.3640	0.1000
	Heat	0.6986	0.5581
13	Electricity	0.8413	0.2000
	Wind	0.1796	0.3534
	Solar	0.1013	0.4012
	Gas	1.1775	0.4040
Total Cost (mu)		**5052.0203**	5603.9056
Total Loss (pu)		2.2539	**2.1126**

Case-3: Minimization of total energy hub cost

In this case, the objective was to minimize the total EH cost. From Table 9, the result of the LSHADE algorithm was 5016.7876 mu, yielding 35.2327 mu more than the best result by the proposed algorithm. However, the total cost with the proposed FDB-LSHADESPACMA algorithm was 5052.0203 mu which is the best result among the results of the MPA (5311.7039 mu), EO (5539.9438 mu), BMO (5298.9759 mu), AEFA (5183.8137 mu), AEO (5535.9251 mu), SDO (5535.9251 mu), AGDE (5246.6165 mu), COA (5193.8526 mu), SSA (5444.5390 mu), LSHADESPACMA (5054.1576 mu), MFO (5407.3923 mu), GSA (5500.1353 mu), and GA (5452.2800 mu) algorithms. Furthermore, according to Table 9, the FDB-LSHADESPACMA algorithm achieved the lowest mean value with 5170.4820 mu among all algorithms.

Case-4: Minimization of energy hub loss

In this case, the objective was to minimize the total EH loss. From Table 9, the minimum objective value was obtained by COA with 2.1004 pu, which was the minimum total loss value compared to the FDB-LSHADESPACMA (2.1126 pu), MPA (2.2216 pu), EO (2.1462 pu), BMO (2.1186 pu), AEFA (2.1666 pu), AEO (2.2105 pu), SDO (2.1557 pu), AGDE (2.2306 pu), SSA (2.2127 pu), LSHADESPACMA (2.1176 pu), MFO (2.1726 pu), LSHADE (2.2755 pu), GSA (2.2203 pu), and GA (2.1509 pu) algorithms. The FDB-LSHADESPACMA algorithm was the second best algorithm after the LSHADE algorithm. In addition, when the results given in Table 9 were evaluated, the best mean total loss value was yielded by the proposed algorithm.

4.2.3. Results of the Test System-3

Test System-3 includes the 7 EH structures and the data of the test system are given in in Table 5. Two case studies were considered using this test system. The optimal solutions of the Case-5 and Case-6 obtained by proposed algorithm are given in Table 8.

Table 8. The optimal solutions for Case-5 and Case-6 obtained by proposed algorithm [37]

Hub No	Input Energy	Case-5	Case-6
1	Electricity	0.7494	0.7420
3	Solar	0.4390	0.2183
	Gas	0.9806	1.7998
4	Electricity	1.1266	1.1744
	Solar	0.3062	0.1164
	Gas	0.8634	0.8430
6	Wind	0.5204	0.5210
	Gas	0.9044	1.1000
8	Wind	0.4824	0.7497
	Solar	0.3246	0.4925
	Gas	1.7981	1.2875
	Heat	0.8992	0.6616
14	Electricity	1.6699	2.0545
	Wind	0.4671	0.1008
	Solar	0.2801	0.4937
	Gas	0.1012	1.7349
15	Electricity	0.7493	0.4577
	Wind	0.3186	0.6000
	Gas	0.2015	0.2708
	Heat	0.1019	0.6980
Total Cost (mu)		**5217.2151**	6311.5784
Total Loss (pu)		2.9401	**2.7051**

Case-5: Minimization of total energy hub cost

In this case, the aim was to minimize the total EH cost. From Table 9, the LSHADE algorithm achieved the lowest cost value with 5193.6270 mu. The results of the other algorithms were the FDB-LSHADESPACMA (5217.2151 mu), MPA (5428.6760 mu), EO (5438.3641 mu), BMO (5492.5474 mu), AEFA (5624.2177 mu), AEO (5592.9273 mu), SDO (5517.0042 mu), AGDE (5300.4345 mu), COA (5318.3889 mu), SSA (5711.0993 mu), LSHADESPACMA (5218.9763 mu), MFO (5512.5763 mu), GSA (5771.0521 mu), and GA (5442.6938 mu) algorithms. Moreover, the LSHADE algorithm ranked first among its competitors in terms of both minimum and mean fitness function values. The proposed algorithm followed the LSHADE and ranked second for both minimum and mean fitness function values.

Case-6*: *Minimization of energy hub loss

The aim of this case was to minimize the total EH loss in this case. From Table 9, the minimum fitness values were

FDB-LSHADESPACMA (2.7051 pu), MPA (2.8031 pu), EO (2.7832 pu), BMO (2.7399 pu), AEFA (2.8098 pu), AEO (2.8086 pu), SDO (2.8106 pu), AGDE (2.7998 pu), COA (2.6882 pu), SSA (2.7988 pu), LSHADESPACMA (2.7170 pu), MFO (2.7762 pu), LSHADE (2.8375 pu), GSA (2.8315 pu), and GA (2.7896 pu) algorithms. These results show that the proposed algorithm was second after the COA algorithm which had the best minimum fitness value. However, it ranked first in terms of the mean fitness value with 2.7372 pu from Table 9.

Table 9. The min, max, mean, and std values by all MHS algorithms for all cases of test systems [37]

Test System	Case		FDB-LSHADESPACMA	LSHADESPACMA	COA	LSHADE	AGDE
Test System-1	Case-1	Min	**3292.2784**	3337.8356	3340.7766	3336.561	3330.6835
		Max	3349.9877	3364.374	3626.2768	3351.1087	3552.9225
		Mean	**3343.1827**	3353.1385	3511.8566	3344.9743	3475.8827
		Std	10.452	6.2062	68.4478	4.7963	48.6772
	Case-2	Min	**1.6753**	1.6833	1.7155	1.8756	1.8236
		Max	1.7353	1.8528	1.9456	2.0752	2.0363
		Mean	**1.716**	1.7802	1.82	2.0258	1.9623
		Std	0.0182	0.0457	0.0671	0.0564	0.0563
Test System-2	Case-3	Min	5052.0203	5054.1576	5193.8526	**5016.7876**	5246.6165
		Max	5201.9358	5233.3845	5493.9772	5206.7568	5504.8776
		Mean	**5170.482**	5189.5146	5386.5036	5178.7296	5405.1501
		Std	39.3372	47.9793	92.51	36.4988	65.8468
	Case-4	Min	2.1126	2.1176	**2.1004**	2.2755	2.2306
		Max	2.1706	2.2352	2.3012	2.381	2.338
		Mean	2.**1461**	2.1922	2.2158	2.3562	2.2942
		Std	0.0198	0.0325	0.051	0.0212	0.032
Test System-3	Case-5	Min	5217.2151	5218.9763	5318.3889	**5193.627**	5300.4345
		Max	5258.1804	5317.4979	5538.3283	5263.4826	5546.7985
		Mean	5243.6879	5279.007	5469.9934	**5239.3687**	5474.6452
		Std	13.1156	26.9089	58.765	20.3962	52.9214
	Case-6	Min	2.7051	2.717	**2.6882**	2.8375	2.7998
		Max	2.7524	2.7848	2.8525	2.8916	2.8871
		Mean	**2.7372**	2.7541	2.8109	2.8822	2.8603
		Std	0.0135	0.0199	0.0326	0.0113	0.0199

4.2.4. Statistical analysis

The performances of the proposed FDB-LSHADESPACMA and fourteen MHS algorithms were analyzed using Friedman test on nine case studies. The Friedman test was performed based on the mean of the fitness function values for 30 runs. Friedman ranks of all algorithms for nine different case studies are presented in Table 10. The mean rank of the algorithms was listed in the last column. When examined the results given in Table 10, FDB-LSHADESPACMA ranked first among the all algorithms in 5 of 6 cases studies. When the results given in Table 10 were evaluated in terms of the mean rank value, FDB-LSHADESPACMA ranked first and showed a superior performance compared to its competitors. When the base LSHADESPACMA algorithm ranked second, the COA algorithm ranked third in terms of mean rank value.

Table 10. Friedman ranks of all meta-heuristic algorithm for test systems [37]

Algorithm	Test System-1		Test System-2		Test System-3		Mean Rank
	Case-1	Case-2	Case-1	Case-2	Case-1	Case-2	
FDB-LSHADESPACMA	**1.2667**	**1.0000**	**1.2333**	**1.0333**	1.7667	**1.0333**	**1.2222**
LSHADESPACMA	3.0667	2.1000	2.8333	2.1667	3.0000	2.0333	2.5333
COA	5.0000	3.2000	4.4667	2.8000	4.4333	2.9667	3.8111
AGDE	4.0333	7.1000	4.6333	8.1333	4.5667	8.9667	6.2389
LSHADE	1.8000	13.300	1.9333	14.6333	**1.2333**	12.5333	7.5722
BMO	11.8333	5.0000	9.7333	4.7333	9.3333	5.7667	7.7333
MPA	6.7667	10.4667	6.0333	6.3667	6.2333	12.3667	8.0389
GA	12.2333	7.0000	8.8667	10.3000	6.8333	6.5	8.6222
SDO	6.7333	11.5333	7.1000	11.1667	8.1667	7.4667	8.6945
EO	13.6000	5.2667	12.0000	5.4667	9.4667	9.9	9.2834
MFO	9.9667	8.0667	13.2333	9.8333	10.9667	10.7333	10.4667
AEO	12.9000	10.6000	10.9333	12.6000	12.6333	5.7667	10.9056
SSA	12.6000	11.3000	10.0333	9.2667	14.8000	8.6	11.1000
AEFA	8.8000	9.7667	14.1667	10.9667	12.4667	14.6333	11.8000
GSA	9.4000	14.3000	12.8000	10.5333	14.1000	10.7333	11.9778

5. Conclusions

In this paper, Fitness-Distance-Balance based LSHADESPACMA (FDB-LSHADESPACMA) algorithm was proposed to solve the EH optimization problems. The following conclusions was obtained as a result of this study:

- *The novel EH test systems were introduced to the literature*: An energy hub model was proposed, where the input energy carriers were electricity, wind energy, natural gas, solar energy, and heat and the outputs can be electricity, cooling, heat, and compressed air. Based on them, 16 EH structures were created and three different scale of the EH test systems were introduced to the literature.
- *A strong MHS algorithm was proposed for the solution of the optimization problems*: The guide used in the mutation strategy of the LSHADESPACMA was redesigned by using the FDB method. Four variations of the LSHADECPACMA were created and tested on the CEC2017 and CEC2020 benchmark problems in three dimensional (30/50/100) search space. The best variation was determined and used in the rest of the studies.
- *The proposed algorithm was applied to the solution of the EH optimization problems*: In this study, two objective functions were considered: (*i*) minimization of total cost and (*ii*) minimization of total loss. Using the three test systems and two objective functions, six case studies were carried out. The results of the proposed algorithm were compared to the 14 competing MHS algorithms. The Friedman test were applied to the results of the case studies for comparing the performance of the proposed algorithm. According to the Friedman results, the proposed algorithm ranked first with 1.2926 score value among them.

To sum up, these results demonstrate that the proposed algorithm outperformed the its rivals in solving in solving EH optimization problems.

6. References

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