Fitness Distance Balance Based Tasmanian Devil Optimization Algorithm for Solving Economic Dispatch Problem with Integrated Wind Power

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***Abstract*— Fossil fuel-based energy sources are used for power generation in power systems and these energy sources have negative impacts on the ecological system. Progress is being made to protect the ecological balance with the increasing use of renewable energy. Therefore, in the study conducted, an Economic Dispatch approach is presented for integrated wind energy, one of the renewable energy resources. Weibull Probability Density Function (PDF) is used to estimate the wind energy since it is not continuous and regular. In the study, the Fitness Distance Balance Based Tasmanian Devil Optimization Algorithm (FDBTDO) was used to solve this problem. This system was evaluated as a power system comprising of conventional thermal generators and one of the most important renewable energy resources, which are wind power generators. The simulation results produced by FDBTDO were compared with the simulation results produced by TDO. As a result of the study, it was observed that the results produced by FDBTDO were better than the results produced by TDO.**

***Keywords* — Fitness Distance Balance, Tasmanian Devil Optimization Algorithm, Economic Dispatch, Renewable Energy Resources, Wind Power.**

I. INTRODUCTION

Electrical energy is recognized as a fundamental element in the economic and social development of modern societies. The increasing demand for electricity with technological developments and industrialization has revealed the necessity of efficient resource allocation in energy systems [1, 2, 7]. The Economic Dispatch (ED) problem has become a critical optimization issue in the power sector in order to meet demand and comply with various system constraints while minimizing costs in electricity generation [1, 2, 5, 8, 10]. In addition, ED has a fundamental role in ensuring the reliability and security of electric power systems and is a complex optimization problem that aims to optimize generation units to meet the system demand at the lowest cost [2, 12, 13].

Problems such as the scarcity of fossil fuels, increasing fuel costs and global environmental pollution necessitate the integration of renewable energy sources in electricity generation [1, 3, 4, 6, 12]. The inclusion of resources such as wind and solar energy in electricity generation systems necessitates new modelling and optimization methods to increase the predictability of these non-continuous resources. In this context, methods such as Weibull PDF are widely used in wind speed forecasts [1].

In recent years, intensive research has been carried out on the optimization of the ED problem, and modern methods such as artificial intelligence and heuristic algorithms have been effectively used to solve ED problems [5, 11]. In this context, the study aims to provide more efficient and sustainable energy solutions by examining the optimization techniques of the economic load balancing problem.

Numerous optimization techniques have recently been applied to the Wind Power Integrated Economic Dispatch Problem like Coyote Optimization Algorithm [1], Butterfly Optimization Algorithm [3], Equilibrium Optimizer [8], Social Optimization Algorithm [9], Improved Symbiosis Particle Swarm Optimization [10], Novel Quantum-Behaved Particle Swarm Optimization Algorithm [11], Bat Optimization Algorithm [12], Arithmetic Optimization Algorithm [13], Wait-and-See approach [14], Cuckoo Search Algorithm [15], Diffusion Particle Optimization [16].

Tasmanian Devil Optimization (TDO) algorithm is a novel bio-inspired metaheuristic algorithm and emulates the behavior of Tasmanian devils, which has been developed by Dehghani, Hub`lovský and Trojovský in 2022[17]. Tasmanian devils can either attack live prey or consume the carcasses of dead animals. FDB was created to solve the meta-heuristic search (MHS) process' premature convergence issue [18]. Fitness Distance Balance (FDB) is implemented into the TDO algorithm to contribute better to the solution of the problem. The TDO algorithm's exploration capabilities were augmented, establishing a robust balance between exploitation and exploration by the implementation of FDB, a newly devised and effective selection method for constructing the TDO algorithm. Solution candidates that direct the TDO algorithm's search process could be chosen more successfully by applying the FDB approach, just like in nature.

This paper proposes a wind power integrated economic dispatch model aimed at optimizing the fuel costs of power plants comprising both thermal and wind energy sources. To achieve this objective, the FDBTDO algorithm has been employed on the test system to address the issue. The FDBTDO algorithm has exhibited successful results. The subsequent sections of the paper are organized as follows. The problem

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formulation of the system, which incorporates both thermal and wind power generators, is described in section II. The proposed FDBTDO algorithm is explained in Section III. Section IV presents the findings of the experiment. Section V contains the conclusions.

II. Problem Definition

The primary aim of the optimization problem presented in this article is to reduce operational costs within an energy system comprising wind and thermal generation units. In line with this goal, efforts are being made to reduce fossil fuel consumption and associated costs by ensuring the most efficient use of renewable energy sources. At the same time, optimal production planning is carried out with consideration of the system's reliability and sustainability [1].

A. Cost Function of Thermal Generators

Thermal units' cost function is computed using (1).

$$F_{TH} = \sum_{i=1}^{N} F_i\left(P_i\right) = \alpha_i + \beta_i P_i + \theta_i P_i^2 \tag{1}$$

In the formula, the term F_{TH} represents the total fuel cost of thermal generators, while the expression $F_i(P_i)$ represents the fuel cost function for the P_i generator. Here, P_i represents the active power produced by the ith generator. The parameters α_i, β_i, and θ_i are the fuel cost coefficients. The total number of thermal generators in the system is represented by N [1].

B. Cost Function for Wind Power Generators

In systems where wind and thermal generators function simultaneously, uncertainty in the wind speed must be considered when assessing the costs of wind energy. Given these uncertainties, the expenses caused from excessive production due to overestimation and the expenses incurred from insufficient production due to underestimation must also be considered [19]. The cost function of the wind power considering overestimation and underestimation conditions can be expressed as follows:

$$F_W = \sum_{j=1}^{M} \mathrm{Cost}W_{dir,j} + \mathrm{Cost}W_{oe,j} + \mathrm{Cost}W_{ue,j} \tag{2}$$

Here, $CostW_{dir,j}$ represents the direct cost of wind power, $CostW_{oe,j}$ represents the overestimated cost of wind power, and $CostW_{ue,j}$ represents the underestimated cost of wind power. According to [20], $CostW_{dir}$, $CostW_{oe}$, and $CostW_{ue}$ cost functions are calculated by (3), (4) and (5), respectively [1].

$$\mathrm{Cost}W_{dir} = \sum_{j=1}^{M}\left(q_j \times w_j\right) \tag{3}$$

$$\mathrm{Cost}W_{oe} = \sum_{j=1}^{M}\left(C_{rwj} \times E\left(Y_{oe,j}\right)\right) \tag{4}$$

$$\mathrm{Cost}W_{ue} = \sum_{j=1}^{M}\left(C_{pwj} \times E\left(Y_{ue,j}\right)\right) \tag{5}$$

The terms q_j, w_j, C_{rwj}, and C_{pwj} in the formulas represent the direct cost coefficient, the power generated by the jth wind generator, and the overestimation and underestimation cost coefficients for the relevant generator, respectively. In addition, the terms $E(Y_{oe,j})$ and $E(Y_{ue,j})$ represent the expected wind power of the jth generator in the overestimation and underestimation cases, respectively, and these quantities are defined by (6) and (7).

$$\begin{aligned}\mathrm{E}\left(\mathrm{Y_{oe,j}}\right) &= \mathrm{w_j}\left[1\text{-}\exp\left(-\frac{\mathrm{v_{in,j}^{k_j}}}{\mathrm{c_j^{k_j}}}\right)+\exp\left(-\frac{\mathrm{v_{out,j}^{k_j}}}{\mathrm{c_j^{k_j}}}\right)\right]+\\ &\left(\frac{\mathrm{w_{r,j}v_{in,j}}}{\mathrm{v_{r,j}\text{-}v_{in,j}}}+\mathrm{w_j}\right)\left[\exp\left(-\frac{\mathrm{v_{in,j}^{k_j}}}{\mathrm{c_j^{k_j}}}\right)\text{-}\exp\left(-\frac{\mathrm{v_{1,j}^{k_j}}}{\mathrm{c_j^{k_j}}}\right)\right]+\\ &\left(\frac{\mathrm{w_{r,j}c_j}}{\mathrm{v_{r,j}\text{-}v_{in,j}}}\right)\left[\Gamma\left(1+\frac{1}{\mathrm{k_j}},\left(\frac{\mathrm{v_{1,j}}}{\mathrm{c_j}}\right)^{\mathrm{k,j}}\right)\text{-}\Gamma\left(1+\frac{1}{\mathrm{k_j}},\left(\frac{\mathrm{v_{in,j}}}{\mathrm{c_j}}\right)^{\mathrm{k,j}}\right)\right]\end{aligned} \tag{6}$$

$$\begin{aligned}\mathrm{E}\left(\mathrm{Y_{ue,j}}\right) &= \left(\mathrm{w}_{r,j}\text{-}\mathrm{w_j}\right)\left[\exp\left(-\frac{\mathrm{v_{r,j}^{k_j}}}{\mathrm{c_j^{k_j}}}\right)+\exp\left(-\frac{\mathrm{v_{out,j}^{k_j}}}{\mathrm{c_j^{k_j}}}\right)\right]+\\ &\left(\frac{\mathrm{w_{r,j}v_{in,j}}}{\mathrm{v_{r,j}\text{-}v_{in,j}}}+\mathrm{w_j}\right)\left[\exp\left(-\frac{\mathrm{v_{r,j}^{k_j}}}{\mathrm{c_j^{k_j}}}\right)\text{-}\exp\left(-\frac{\mathrm{v_{1,j}^{k_j}}}{\mathrm{c_j^{k_j}}}\right)\right]+\\ &\left(\frac{\mathrm{w_{r,j}c_j}}{\mathrm{v_{r,j}\text{-}v_{in,j}}}\right)\left[\Gamma\left(1+\frac{1}{\mathrm{k_j}},\left(\frac{\mathrm{v_{1,j}}}{\mathrm{c_j}}\right)^{\mathrm{k,j}}\right)\text{-}\Gamma\left(1+\frac{1}{\mathrm{k_j}},\left(\frac{\mathrm{v_{r,j}}}{\mathrm{c_j}}\right)^{\mathrm{k,j}}\right)\right]\end{aligned} \tag{7}$$

Here, c_j and k_j represent the scale and shape factors of the jth wind generator, and these values are included in the Weibull PDF used in wind speed estimation. In addition, the terms $v_{in,j}$, $v_{r,j}$ and $v_{out,}j$ represent the *cut-in*, *rated* and *cut-out* wind speeds, respectively [21].

In this study, the objective function to be used for testing the proposed algorithm is the economic dispatch problem integrated with wind power, which has been formulated as follows:

$$\min F_{Total} = F_{TH} + F_W \tag{8}$$

C. System Constraints

The constraints for the objective function to be minimized are divided into three: load-generation balance, real power generation constraint, and prohibited operating zone constraint

[1].

1) Load-Generation Balance

$$\sum_{i=1}^{N} P_i = P_D + P_L \tag{9}$$

P_D and P_L represent the total demanded power and total power loss, respectively.

$$P_L = \sum_{i=1}^{N_G}\sum_{j=1}^{N_G} P_{Gi} B_{ij} P_{Gj} + \sum_{j=1}^{N_G} P_{Gi} B_{i0} P_{00} \tag{10}$$

2) Real Power Generation Constraint

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{11}$$

where, P_i^{min} and P_i^{max} are minimum and maximum power limits.

3) Prohibited Operating Zone Constraint

$$P_i \in \left\{ \begin{array}{c} P_i^{\min} \le P_i \le P_{i,1}^{l} \\ P_{i,j-1}^{u} \le P_i \le P_{i,j}^{l} \\ P_{i,POZ_i}^{u} \le P_i \le P_i^{\max} \end{array} \right\} \; j = 2,3,\ldots,POZ_i \tag{12}$$

The values of $P_i^{u}{}_{,POZ}$ and $P_i^{l}{}_{,j}$ indicate the lower and upper limits of the *j*th forbidden zone, respectively [1].

Other losses are neglected for this problem.

III. Fitness Distance Balance Based Tasmanian Devil Optimization Algorithm

A. Tasmanian Devil Optimization Algorithm

1) Mathematical Modeling

The design of the Tasmanian Devil Optimization has been influenced by the Tasmanian devil's feeding strategies, which involve foraging or locating carcasses. Mathematical modeling of optimal solutions is made possible by these feeding behaviors, which are analogous to the monster's search for food and are used to find optimal solutions in optimization issues [17].

2) Initialization

The stochastic approach known as Tasmanian Devil Optimization (TDO) uses randomly produced Tasmanian devils as search agents to solve problems. Based on their locations in the search space, which is represented by (13), the population is created for problem variables [17].

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{Nxm} = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ x_{N1} & \cdots & x_{Nj} & \cdots & x_{Nm} \end{bmatrix}_{Nxm} \tag{13}$$

The *i*th candidate solution is denoted by X_i in matrix X, which represents the Tasmanian devil population. X_{ij} denotes the proposed candidate value for the *j*th variable. The number of Tasmanian devils is denoted by N, and the number of variables in the problem being addressed is denoted by m.

The objective function value of each candidate solution is determined by substituting the variable values of the respective candidate solution into the objective function. Equation (14) can be used to model the objective function values obtained in this manner [17].

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{Nx1} = \begin{bmatrix} F(x_1) \\ \vdots \\ F(x_j) \\ \vdots \\ F(x_N) \end{bmatrix}_{Nx1} \tag{14}$$

The F vector contains the calculated results of the objective function. The fitness value of the *i*th solution is denoted by the F_i. The optimal solution is regarded as the most effective in the population and is revised at each iteration. The TDO algorithm's population update mechanism is based on Tasmanian devils' two primary feeding strategies: hunting and scavenging. Each Tasmanian demon is updated in accordance with one of these strategies [17].

a) Strategy 1: Scavenging (Exploration Phase)

Sometimes, the Tasmanian devil, a predatory animal, consumes carcasses within its territory as opposed to foraging. Tasmanian devils exhibit behavior that is comparable to an algorithmic approach to problem-solving, in which they conduct habitat searches for carcasses. Equations (15) to (17) mathematically symbolize the Tasmanian devil's scavenging strategy. In the TDO algorithm, the coordinates of other individuals in the search space are used to determine potential carcass places for each Tasmanian devil. Equation (15) simulates the random selection of one of these prospective carcasses, with k representing a randomly selected individual that is chosen as the target carcass for the *i*th Tasmanian devil. From *1* to N, the value of k should be randomly selected, but it should not be equal to the value of i [17].

$$C_i = X_k,\ i = 1,2,\ldots,N,\ k \in \{1,2,\ldots,N \,|\, k \ne i\} \tag{15}$$

C_i represents the carcass selected by *i*th individual. A new location in the search space for the Tasmanian devil is

determined based on the carcass that has been selected. In the simulation of the Tasmanian devil's movement in this strategy, the Tasmanian devil moves toward the carcass if the objective function value is higher; conversely, it retreats if the value is lower. The mobility strategy of the Tasmanian devil has been modeled in (16). In the final phase of the initial strategy, the Tasmanian devil is allocated a new place if the objective function's value is superior at this new location. Alternatively, the Tasmanian devil is maintained in its prior position. This update phase is represented in (17) [17].

$$x_{ij}^{newS1} = \begin{cases} x_{ij} + r.\left(c_{ij} - I.x_{ij}\right), & F_{C_i} < F_i \\ x_{ij} + r.\left(x_{ij} - c_{ij}\right), & otherwise \end{cases} \quad (16)$$

$$X_i = \begin{cases} X_i^{newS1}, & F_i^{newS1} < F_i \\ X_i, & otherwise \end{cases} \quad (17)$$

In this context, X_i^{newS1} represents the new candidate solution of the first Tasmanian devil in accordance with the first strategy, x_{ij}^{newS1} represents the value of the *j*th variable, F_i^{newS1} is the objective function value, F_{Ci} is the value of the objective function of the chosen carcass, *r* is a random number within the range of [0, 1], and *I* is a random number that can vary between 1 and 2 [17].

b) Strategy 2: Feeding by Eating the Prey (Exploitation Phase)

In order to pursue and consume its prey, the Tasmanian Devil implements an additional foraging strategy. It employs a two-step attack strategy: First, it scans the environment, identifies the target, and strikes it. Subsequently, it pursues prey to halt its progress and commence consuming. The initial phase of prey selection and assault is represented by using (18) to (20), while the second strategy posits the positions of other population members as the prey. The *k*th member of the population is randomly designated as prey, where *k* is a natural random number between *1* and *N*. (18) simulates the process of selecting prey [17].

$$P_i = X_k,\ i = 1,2,\ldots,N,\ k \in \left\{1,2,\ldots,N \middle| k \neq i\right\} \quad (18)$$

where P_i is the prey selected by *i*th Tasmanian devil.

The selection process similar to *Strategy 1* is also held on this strategy according to (19) and (20).

$$x_{ij}^{newS2} = \begin{cases} x_{ij} + r.\left(p_{ij} - I.x_{ij}\right), & F_{P_i} < F_i \\ x_{ij} + r.\left(x_{ij} - p_{ij}\right), & otherwise \end{cases} \quad (19)$$

$$X_i = \begin{cases} X_i^{newS2}, & F_i^{newS2} < F_i \\ X_i, & otherwise \end{cases} \quad (20)$$

where, X_i^{newS2} represents the *i*th individual in accordance with the second strategy, x_{ij}^{newS2} signifies the value of the *j*th variable, F_i^{newS2} is the objective function value, F_{Pi} is the objective function value of the selected prey [17].

B. Fitness Distance Balance Method

The Fitness Distance Balance (FDB) selection approach seeks to identify candidates that will most significantly enhance the search process within a population in a steady and efficient manner. This technique aims to conduct the exploration process, facilitating the identification of diverse regions within the search space, and the exploitation process, utilizing prior fitness information, in a balanced manner [18].

In the initial stage of the FDB technique, the distance of the candidate solutions from the optimal solution (P_{best}) is computed. The designated objective function, P-population, and Euclidean metric are employed to compute the distance of each member to P_{best} as seen in (21). The distance vector D_P formulated for possible solutions is presented in (22) [18].

$$\forall_{i=1}^{n}, P_i \neq P_{best}, D_{Pi} = \sqrt{\left(x_{1P_i} - x_{1P_{best}}\right)^2 + \left(x_{2P_i} - x_{2P_{best}}\right)^2 + \cdots + \left(x_{mP_i} - x_{mP_{best}}\right)^2} \quad (21)$$

$$D_P \equiv \begin{bmatrix} d_1 \\ \vdots \\ d_n \end{bmatrix}_{n\times 1} \quad (22)$$

In the second phase of the FDB approach, the scores of the solution candidates are computed. This calculation employs normalized fitness values (*normF*) and normalized distance values ($normD_P$). The purpose for using normalized values is to avert the dominance of one parameter over the other [18].

A weight coefficient (*w*) is used to evaluate the impact of fitness and distance variables in score computation. In this study, *w=0,5* has been established for this coefficient, which was selected within the range *0<w<1*. Equation (23) can be used to calculate scores in the FDB selection procedure [18].

$$\forall_{i=1}^{n}, P_i, S_{Pi} = \omega * normfv_i + (1-\omega) * normD_{Pi} \quad (23)$$

The score vector is calculated as follows:

$$S_P \equiv \begin{bmatrix} s_1 \\ \vdots \\ s_n \end{bmatrix}_{n\times 1} \quad (24)$$

C. Fitness Distance Balance Based Tasmanian Devil Optimization Algorithm

Instead of using the k value to choose an individual at random from the population in the Tasmanian devil optimization algorithm's *Strategy 1* and *Strategy 2* phases, both strategies employed the index *k* value that was established by

the FDB selection method. As a result, (15) and (18) are updated as follows:

$$C_i = X_{fdb},\ i = 1,2,\ldots,N,\ k \in \{1,2,\ldots,N \mid fdb \neq i\} \quad (25)$$

$$P_i = X_{fdb},\ i = 1,2,\ldots,N,\ k \in \{1,2,\ldots,N \mid fdb \neq i\} \quad (26)$$

IV. Results

In this section, analyses have been conducted to measure the performance of the developed FDBTDO algorithm. In literature, real-life problems are frequently used to measure the effectiveness of optimization algorithms. In this study, the wind power integrated economic dispatch problem, which is a real-life problem, was solved using the proposed algorithm, and the results obtained were compared with the original algorithm. For the evaluation process, two different test systems with 6 and 12 generators were established. In the simulation study, the maximum number of iterations was set to 500, the population size was taken as 50 for both algorithms, and to ensure a fair comparison, both algorithms were run independently 30 times for each case. Additionally, the cut-in, rated, and cut-out speeds for the wind turbines in the wind power plants, which are separately located in both systems, were determined as V_{in}=3m/s, V_r=16m/s, and V_{out}=25m/s, respectively. Furthermore, for the Weibull PDF distribution method used in wind power calculations, the shape and scale factor values were taken as k=2 and c=9, respectively [1].

A. Case 1

In this case, a system consisting of 5 thermal generators and 1 wind power plant, totaling 6 generators, was used to solve the algorithms. The last thermal generator in the system has been replaced with a wind power plant. Load demand from the system has been determined to be 610 MW. The power loss that occurred in the system has been taken into account for this situation. Additionally, the cost coefficients used in the cost calculations of the 5 thermal generators were taken from ref [22].

Alongside direct costs, penalty costs and reserve costs have been factored into the cost calculations for the wind power plant, which was integrated into the system. The penalty cost coefficient (C_{pwj}) is determined as 1,5. Likewise, the reserve cost coefficient (C_{rwj}) is established as *3*. The rated power (P_r) value for every single wind turbine was taken as *3 MW*, and the total rated power value of the 25 wind turbines located in the wind farm was 75 MW. Consequently, the values obtained as a result of the optimization processes carried out using the TDO and FDBTDO algorithms are presented in Table 1.

TABLE I: Comparison of TDO and FDBTDO Algorithms for Case 1

	Min	Max	TDO	FDBTDO
P1	10	75	12.3383	10.0000
P2	20	125	98.2228	98.5398
P3	30	175	112.7313	112.6735
P4	40	250	124.9077	209.8158
P5	50	300	229.4480	139.7598
PW	0	75	39.3622	46.1228
Total Loss (MW)			7.0004	6.9117
Wind Cost ($/h)			116.9412	129.4315
Thermal Cost ($/h)			1598.4521	1568.6718
Total Cost ($/h)			1715.4031	**1698.1033**

When the values in Table I are examined, it is observed that the proposed FDBTDO algorithm yields better results than the TDO algorithm in terms of total cost value, with a value of 1698.1033 $/h. Additionally, the convergence curve graph belongs to the two algorithms is provided in Fig. 1.

The minimum, mean, maximum, and standard deviation values obtained from 30 independent runs are presented in Table II. According to the values in the table, it is observed that the FDBTDO algorithm is superior to the TDO algorithm in both minimum and mean values for Case 1.

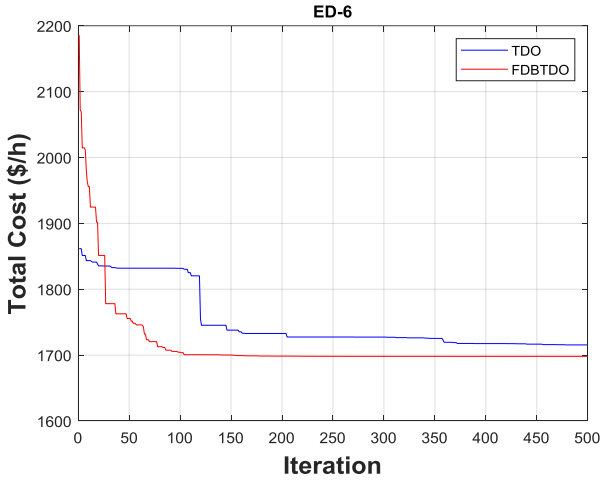

Fig. 1. Convergence curves of the cost values for TDO and FDBTDO algorithms for Case 1.

TABLE II: Min, Mean, Max, and STD Values for Case 1

Algorithms	Min	Mean	Max	STD
TDO	1715.403	1784.783	1886.467	42.825
FDBTDO	**1698.103**	**1699.606**	**1703.539**	**1.921**

B. Case 2

In this case, the TDO and FDBTDO algorithms were employed to solve the system, which comprises 10 thermal generators and 2 wind power plants, for a total of 12 generators. In this system, the last two thermal generators have been replaced with wind power plants. The power loss occurring in the system has been neglected for this case. The system's load demand has been taken as 1750 MW. Additionally, the cost coefficients used in the cost calculations of the 10 thermal generators have been taken from ref [23].

TABLE III: COMPARISON OF TDO AND FDBTDO ALGORITHMS FOR CASE 2

	Min	Max	TDO	FDBTDO
P1	150	470	378.0372	379.5488
P2	135	460	396.6631	396.9189
P3	73	340	339.9825	303.8991
P4	60	300	60.3619	60.8554
P5	73	243	73.0526	73.5502
P6	57	160	159.9505	158.5389
P7	20	130	129.9392	129.5898
P8	47	120	47.0906	47.1053
P9	20	80	20.2338	20.0320
P10	55	55	55.0000	55.0000
PW1	0	50	49.9584	49.9931
PW2	0	75	39.7300	74.9446
Wind Cost ($/h)			2055.8328	2808.8640
Thermal Cost ($/h)			42072.3522	41075.7339
Total Cost ($/h)			44128.1852	**43884.6217**

For the system's wind power plants, the reserve cost coefficient is $C_{pwj}=4,5$ while the penalty cost coefficient is $C_{rwj}=9$. The rated power value for each wind turbine is taken as $P_r=5$ *MW*, and the total rated power value of the 10 and 15 wind turbines located in the wind farms is determined as 125 MW. Based on this information, the values obtained as a result of the optimization processes carried out with the TDO and FDBTDO algorithms are presented in Table III.

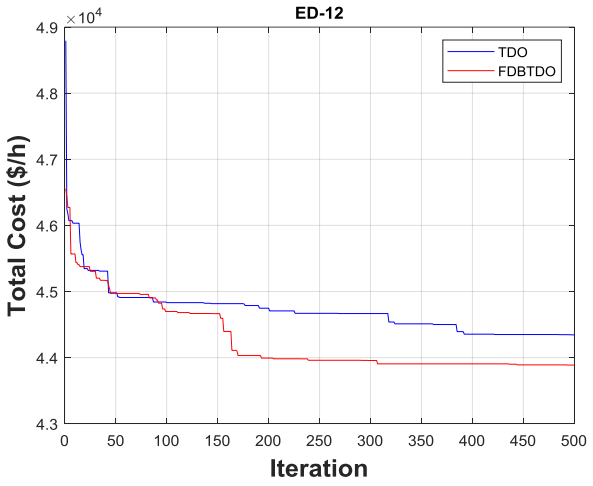

Fig. 2. Convergence curves of the cost values for TDO and FDBTDO algorithms for Case 2.

Upon examination of the values in Table III, it is evident that the proposed FDBTDO algorithm produces superior results in terms of the total cost value, with a value of 43884.6217 $/h. Furthermore, the convergence curve graph for the two algorithms is presented in Fig. 2.

TABLE IV: MIN, MEAN, MAX, AND STD VALUES FOR CASE 1

Algorithms	Min	Mean	Max	STD
TDO	44128.185	44615.604	44986.550	163.939
FDBTDO	**43884.622**	**44223.358**	**44379.942**	**133.040**

Table IV presents the minimum, mean, maximum, and standard deviation values derived from 30 runs. In Case 2, the data indicates that the FDBTDO algorithm outperforms the TDO algorithm in terms of both minimum and mean values.

V. CONCLUSION

In this study, the Tasmanian Devil Optimization (TDO) algorithm has been improved with Fitness Distance Balance (FDB). The newly developed FDB-TDO algorithm has been applied to solve the wind power integrated economic dispatch problem. Due to the uncertainties in wind energy, Weibull PDF was used to solve the optimization problem. Underestimation and overestimation of wind power are included in the cost function. The newly developed FDB-TDO algorithm has been applied to various systems consisting of thermal and wind generator units. In addition, the TDO algorithm was applied to these systems. The simulation results obtained were compared. Simulation results show that FDB-TDO has lower fuel cost and better performance than TDO.

REFERENCES

[1] U. Güvenç and E. Kaymaz, "Economic Dispatch Integrated Wind Power Using Coyote Optimization Algorithm," 2019 7th International Istanbul Smart Grids and Cities Congress and Fair (ICSG), Istanbul, Turkey, 2019, pp. 179-183, doi: 10.1109/SGCF.2019.8782354. https://doi.org/10.1109/SGCF.2019.8782354

[2] R. A. Abttan, A. H. Tawafan and S. J. Ismael, "Economic dispatch by optimization techniques", Int. J. of Electrical and Computer Engineering (IJECE), Vol. 12, No. 3, June2022, pp. 2228 - 2241. doi.org/10.11591/ijece.v12i3.pp2228-2241. https://doi.org/10.11591/ijece.v12i3.pp2228-2241

[3] B.N. Alhasnawi, B.H. Jasim, V. Bureš, , B.E. Sedhom, A.N. Alhasnawi, R. Abbassi, M.R.M. Alsemawai, P. Siano and J.M. Guerrero, "A novel economic dispatch in the stand-alone system using improved butterfly optimization algorithm", Energy Strategy Reviews, Volume 49, 2023. doi.org/10.1016/j.esr.2023.101135. https://doi.org/10.1016/j.esr.2023.101135

[4] Chen, Xu, Qi Lu, Ye Yuan and Kaixun He. "A novel derivative search political optimization algorithm for multi-area economic dispatch incorporating renewable energy." Energy, volume 300, 2024. doi.org/10.1016/j.energy.2024.131510. https://doi.org/10.1016/j.energy.2024.131510

[5] B. M. Hussein, A. I. Jaber, M. W. Abdulwahhab, H. J. Mohammed and N. V. Korovkin, "Application of Intelligent Optimization Algorithms on Economic Dispatch Problem," 2024 XXVII International Conference on Soft Computing and Measurements (SCM), Saint Petersburg, Russian Federation, 2024, pp. 453-456, doi: 10.1109/SCM62608.2024.10554111. https://doi.org/10.1109/SCM62608.2024.10554111

[6] Marzbani, F.; Abdelfatah, A. Economic Dispatch Optimization Strategies and Problem Formulation: A Comprehensive Review. Energies 2024, 17, 550. doi: doi.org/10.3390/en17030550. https://doi.org/10.3390/en17030550

[7] Yang, W.; Zhang, Y.; Zhu, X.; Li, K.; Yang, Z. Research on Dynamic Economic Dispatch Optimization Problem Based on Improved Grey Wolf Algorithm. Energies 2024, 17, 1491. doi:doi.org/10.3390/en17061491. https://doi.org/10.3390/en17061491

[8] S. Agnihotri, A. Atre and H. K. Verma, "Equilibrium Optimizer for Solving Economic Dispatch Problem," 2020 IEEE 9th Power India International Conference (PIICON), Sonepat, India, 2020, pp. 1-5, doi: 10.1109/PIICON49524.2020.9113048. https://doi.org/10.1109/PIICON49524.2020.9113048

[9] Karimi N., Khandani K., "Social optimization algorithm with application to economic dispatch problem". Int. Trans. Electr. Energ. Syst. 2020; 30:e12593. https://doi.org/10.1002/2050-7038.12593. https://doi.org/10.1002/2050-7038.12593

[10] Zhang, Jianxia, Zhang, Jianxin, Zhang, Feng, Chi, Minglu, Wan, Linbin, “An Improved Symbiosis Particle Swarm Optimization for Solving Economic Load Dispatch Problem”, J. of Electrical and Computer Engineering, 2021, 8869477, 11 pages, 2021. doi: doi.org/10.1155/2021/8869477. https://doi.org/10.1155/2021/8869477
[11] Ping, Li, Sun, Jun, Chen, Qidong, “Solving Power Economic Dispatch Problem with a Novel Quantum-Behaved Particle Swarm Optimization Algorithm”, Mathematical Problems in Engineering, 2020, 9741595, 11 pages, 2020. doi: doi.org/10.1155/2020/9741595. https://doi.org/10.1155/2020/9741595
[12] Roy, R. G., “Economic dispatch problem in power system using hybrid pso and enhanced bat optimization algorithm”, J. of Comp. Mechanics, Power System and Control, 3(3), 27-33, 2020. doi: doi.org/10.46253/jcmps.v3i3.a4. https://doi.org/10.46253/jcmps.v3i3.a4
[13] Hao, WK., Wang, JS., Li, XD. et al., “Arithmetic optimization algorithm based on elementary function disturbance for solving economic load dispatch problem in power system”, Appl. Intell., 52, 11846–11872, 2022. doi: doi.org/10.1007/s10489-021-03125-4. https://doi.org/10.1007/s10489-021-03125-4
[14] X. Liu: “Economic Load Dispatch Constrained by Wind Power Availability: A Wait–and–see Approach”, IEEE Transaction on Smart Grid, vol. 1(3), pp. 347 – 355, 2010. doi: 10.1109/TSG.2010.2057458. https://doi.org/10.1109/TSG.2010.2057458
[15] M. Basu and A. Chowdhury, “Cuckoo search algorithm for economic dispatch”, Energy vol.60, pp.99-108, 2013. doi: doi.org/10.1016/j.energy.2013.07.011. https://doi.org/10.1016/j.energy.2013.07.011
[16] L. Han, C. E. Romero, and Z. Yao, “Economic dispatch optimization algorithm based on particle diffusion,” Energy Convers. Manag., vol. 105, pp. 1251–1260, 2015. https://doi.org/10.1016/j.enconman.2015.08.071
[17] M. Dehghani, Š. Hubálovský and P. Trojovský, “Tasmanian Devil Optimization: A New Bio-Inspired Optimization Algorithm for Solving Optimization Algorithm”, IEEE Access, vol. 10, pp. 19599-19620, 2022, doi: 10.1109/ACCESS.2022.3151641. https://doi.org/10.1109/ACCESS.2022.3151641
[18] Kahraman HT, Aras S, Gedikli E (2020) Fitness-distance balance (FDB): a new selection method for meta-heuristic search algorithms. Knowl-Based Syst 190:105169. doi.org/10.1016/j.knosys.2019.105169. https://doi.org/10.1016/j.knosys.2019.105169
[19] X. Liu and W. Xu, "Minimum Emission Dispatch Constrained by Stochastic Wind Power Availability and Cost," in IEEE Transactions on Power Systems, vol. 25, no. 3, pp. 1705-1713, Aug. 2010, doi: 10.1109/TPWRS.2010.2042085. https://doi.org/10.1109/TPWRS.2010.2042085
[20] B. Mandal, P. K. Roy, and S. Mandal, “Economic load dispatch using krill herd algorithm,” Int. J. Electr. Power Energy Syst., vol. 57, pp. 1–10, 2014. https://doi.org/10.1016/j.ijepes.2013.11.016
[21] J. P. Zhan, Q. H. Wu, C. X. Guo, L. L. Zhang and M. Bazargan, "Impacts of Wind Power Penetration on Combined Economic and Emission Dispatch," IEEE PES ISGT Europe 2013, Lyngby, Denmark, 2013, pp. 1-5, doi: 10.1109/ISGTEurope.2013.6695426. https://doi.org/10.1109/ISGTEurope.2013.6695426
[22] C. K. Panigrahi, P. K. Chattopadhyay, R. N. Chakrabarti, and M. Basu, “Simulated annealing technique for dynamic economic dispatch,” Electr. Power Compon. Syst., vol. 34, no. 5, pp. 577–586, 2006. https://doi.org/10.1080/15325000500360843
[23] P. Lu, J. Zhou, H. Zhang, R. Zhang, and C. Wang, “Chaotic differential bee colony optimization algorithm for dynamic economic dispatch problem with valve-point effects,” Int. J. Electr. Power Energy Syst., vol. 62, pp. 130–143, 2014. https://doi.org/10.1016/j.ijepes.2014.04.028

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