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A novel Invasive Weed Optimization with levy flight for optimization problems: The case of forecasting energy demand

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Abstract

Energy is very important nowadays and it has become essential for human life. More amount of energy is necessary for a community with increased living standards and population. This causes an increase in energy consumption. Energy has become one of the most significant problems across the world today; therefore, it should be generated at the best level. Excessive energy generation makes countries lose money while less amount of energy generation causes crises. Therefore, countries need to adjust their energy demand optimally. It is possible to estimate energy demands of countries by using various applications. This study proposes a new improved algorithm for linear regression models to forecast the energy demand of Turkey. The selected algorithm is Invasive Weed Optimization (IWO) algorithm which has been developed with levy flight called LF-IWO. In the linear regression model, input parameters included data regarding Turkey's gross domestic product (GDP), population, import and export. Turkey's energy demand was estimated for these parameters by using the data between 1979 and 2011. The estimation results obtained from the model were compared with those of similar studies in the literature to measure the performance success of the developed algorithm.

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Keywords: Forecasting energy demand; Invasive Weed Optimization; Levy flight; Optimization

1. Introduction

Growth in population and income is the main reason of the increase in the energy consumption across the world. It is also predicted that population growth significantly affects the increase in global energy demand due to developing industries and urbanization. However, energy demand is increasing day by day as a result of developing technology and increasing population, accordingly energy has become essential for human life. Increasing population and welfare level in the world has considerably boosted energy consumption. The world population, which has increased more than twice since 1950, is expected to grow more by 2050 [1]. These data necessitate solving

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the energy problem. Economical, environmentally friendly and socially sensitive methods including greenhouse gas emission should be used to meet increasing energy demand. Numerous underground and renewable energy sources are used in the world for energy generation. In Turkey, energy is generated according to the share order in generation: natural gas, hydroelectric, hard coal and coke, imported coal, wind, liquid fuels such as diesel fuel and fuel oil, geothermal, biogas and solar energy, respectively. Tiris stated that annual global energy demand was expected to be approximately 1.7% between 2020 and 2030 [2]. A study emphasized that it was significant to create a balance between energy generation and energy consumption because of high energy generation costs [3]. Therefore, planning should be done by considering energy demand and energy generation. These processes are carried out using optimization methods [4,5]. Many studies have been performed to determine the future demand by considering the current increasing energy demand. Chaudhry et al. [6] analyzed Pakistan's data between 1972 and 2012. They indicated that energy demand increased rapidly. Gokten and Karatepe [7] first analyzed the relationship between energy consumption and economic growth in Turkey and then investigated the relationship between the imported main energy sources used to generate electricity and the current accounts balance. Boluk [8] examined Turkey's current status about renewable energy and its renewable energy potential, as well as the effects of renewable energy policies on the energy sector and the national economy. The study concluded: Turkey's energy demand has increased along with rapidly increasing population, rapid urbanization and high growth rates. Yılmaz et al. [9] analyzed the relationship between energy consumption and economic growth in Turkey by using data between 1984 and 2012. Similar to the present study, Geem et al. [10] estimated South Korea's energy demand by developing four scenarios with artificial neural networks (ANNs). Ersel Canyurt et al. [11] predicted the future energy demand using two different genetic methods. Toksarı [12] predicted Turkey's energy demand by using the ant colony approach with three scenarios. Behrang et al. [13] estimated Iran's energy demand by 2030 using the bees algorithm method. Ceylan and Ozturk [14] forecasted energy demand with genetic algorithm (GA) based on the economic data in Turkey. Unler [15] proposed a model using the particle swarm optimization based energy demand forecast to predict energy demand in Turkey more efficiently. Kıran et al. [16] constructed a new hybrid algorithm for estimating Turkey's energy demand using particle swarm optimization (PSO) and ant colony optimization (ACO) algorithms by means of different scenarios. Canyurt et al. [17] performed the transportation energy estimation with the GA approach. Beskirli et al. [18] estimated Turkey's energy demand by 2031 with three scenarios and using differential evolution (DE) algorithm. Deng [19] forecasted China's energy demand using ANNs with four independent variables such as gross domestic product (GDP), population, import and export amounts. Amjadi et al. [20] estimated Iran's electricity demand by developing two different forecasting models with two different meta-heuristic methods based on GDP, population, the number of customers and average electricity price. Tefek et al. [21] presented a new hybrid method for Turkey's energy demand: gravitational search–teaching–learning-based optimization. Bulut and Yildiz [22] approached Turkey's energy demand from a different perspective by using different statistical methods. Assareh et al. [23] estimated Iran's energy demand by 2030 using two different methods: genetic algorithm and particle flock optimization. Yu et al. [24] proposed a new hybrid method to estimate China's energy demand. This hybrid method included PSO and GA. In this study, the IWO algorithm was improved with levy flight and the levy flight IWO (LF-IWO) algorithm was proposed. Based on three scenarios, Turkey's energy demand by 2030 was estimated using the LF-IWO.

2. Invasive Weed Optimization (IWO)

The IWO algorithm is a biologically inspired numerical optimization algorithm that mimics the natural behavior of weeds. The IWO algorithm was developed by Mehrabian and Lucas [25] as a new metaheuristic algorithm in 2006. IWO, which has many advantages such as simplicity of the structure, requiring fewer parameters and very strong robustness, is used to solve general, multidimensional, linear and nonlinear optimization problems. Although the algorithm is simple, it is said to be effective in converging to the optimal solution by using basic features such as seeding, growth and competition in a weed colony [25]. Weeds tend to colonize and find suitable places for growth and reproduction. The population consists of the total number of weeds. The suitability of each herb is determined by how close or far it is from the optimal solution. A series of seeds is produced around each weed, in which high-condition weeds produce more seeds than low-condition weeds. The seeds produced are normally dispersed around the mother grass with the mean equal to zero and different variance. The population is then updated to include all weeds and seeds produced. This process continues until the stopping criterion is met. The

IWO algorithm consists of four basic stages. These are baseline initial population, reproduction, spatial distribution, and competitive exclusion.

Initial population: First, the population is randomly distributed over the D-dimensional solution space, as weeds are randomly generated. The fitness of each herb is calculated. The best and worst fitness values are determined.

Reproduction: The number of seeds produced by each weed is evaluated based on fitness. Each seed has a chance to reproduce, and the reproduction rate ranges from maximum to minimum according to the best to worst fit seed. These seeds then develop into wild plants capable of producing new units. The seed producing weed formula is included in Eq. (1).

$$ot_n = \frac{f - f_{worst}}{f_{best} - f_{worst}} (S_{max} - S_{min}) + S_{min} \tag{1}$$

Here, f is the fitness of the weed considered. f_{worst} and f_{best} are the worst and best fit of the current population, respectively. S_{min} and S_{max} are the minimum and maximum number of seeds, respectively.

Spatial distribution: The seeds produced are randomly distributed over the D-dimensional search space, with random numbers normally having a mean equal to zero but with a variable variance. By randomly scattering these seeds, it is ensured that they are close to the parent plant. However, the standard deviation (σ) of the random function will decrease from a predefined initial value (σ_{init}) to a final value (σ_{final}) at each iteration. Its formula is given in Eq. (2).

$$\sigma_{cur} = \frac{(iter_{max} - iter)^n}{(iter_{max})^n} \left(\sigma_{init} - \sigma_{final}\right) + \sigma_{final} \tag{2}$$

Here, $iter_{max}$ is the maximum number of iterations, σ_{cur} is the standard deviation at the current time step, σ_{init} is the first standard deviation, σ_{final} is the final standard deviation, and n is the modulation index.

Competitive exclusion: After a given iteration, the number of weeds in a colony will exceed the maximum population number with rapid reproduction. During this period, each weed was given a seed production permit. The seeds produced are then allowed to propagate into the search space. When all seeds have found their place in the search space, they line up with their parents (as a colony of weeds). Low fitness weeds are then eliminated to reach the maximum population allowed in a colony. Thus, weeds and seeds are sorted together and those with better fitness survive and are allowed to multiply. This process continues until the maximum iteration or other stopping criteria is reached. The weed with the best fitness is selected as the most suitable solution.

3. The proposed method LF-IWO

Although there are many different IWO variants in the literature, the problem that IWO produces early convergence and inefficient results has still continued. The levy flight method was used to solve these problems and enable IWO to produce more efficient results. With this method, IWO, which cannot perform global search well, can do it more effectively so that it does not stick to the local minimum. Levy flight method is given in Eqs. (3)–(5) [26–28]. The Flowchart of LF-IWO is shown in Fig. 1.

$$W_{new}^{iter+1} = P^{iter} + N\left(0, \sigma_{iter}^2\right) \times Lévy\left(\beta\right) \tag{3}$$

$$Lévy\left(\beta\right) = L_{stepsize} \times N_{randn} \tag{4}$$

$$L_{stepsize} = 0.01 \times \left\{ \frac{N_{randn}}{\left[abs\left(N_{randn}\right)\right]^{\frac{1}{\beta}}} \times \frac{\Gamma\left(1+\beta\right) \times \sin\left(\frac{\pi}{2} \times \beta\right)}{\left[\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}\right]^{\frac{1}{\beta}}} \right\} \tag{5}$$

where $L_{stepsize}$ is the stepsize of Levy flight method, N_{randn} is a random number, P^{iter} is the individual of main weeds at the iterth iteration. $\sum_{new}^{iter+1}$, is the weed generated from the individual at the iter + 1 iteration. N(0, σ_{iter}^2) is a random number generated from normal distribution with average zero and standard deviation. β is a constant value and equal to 1.5.

As a result of using the Levy flight method as the sphere search operator in the spatial propagation, the efficiency of the algorithm in the search space increases. The pseudo-code of the Levy flight method is presented as Algorithm 1 in Fig. 2.

Table 1. The total error values obtained between 1979 and 2005.

Weights	LF-IWO	VS	IWO	DE	HAPE	AAA	ABCVSS	BA	GSA	PSO	ACO	TSA
w1	−59.2269	−59.9676	−57.7420	−55.8991	−55.9091	−55.8991	−55.9091	−57.7676	−53.9784	−55.9022	51.3046	−55.6282
w2	−0.0059	−0.0070	0.0037	0.0038	0.0038	0.0038	0.0038	0.00002	−0.0093	0.0021	0.0124	0.0103
w3	1.9858	2.0019	1.9468	1.9123	1.9126	1.9123	1.9126	1.9549	1.8781	1.9126	1.8102	1.9006
w4	0.4018	0.4051	0.3430	0.3735	0.3734	0.3735	0.3734	0.4023	0.4253	0.3431	0.3524	0.2511
w5	−0.5119	−0.5197	−0.4562	−0.4835	−0.4833	−0.4835	−0.4833	−0.5316	−0.4738	−0.4240	−0.4439	−0.3169
Error	**36.0721**	36.1658	39.1535	41.7120	41.7029	41.7120	41.7029	42.4890	43.6001	42.6139	45.7239	46.2783

Table 2. The comparison of the energy estimations of IWO, GSA, and VS models between 1996 and 2005 (E: Estimate, RE: Relative errors).

Year	OED	PM (E)	PM errors	PM RE (%)	VS (E)	VS errors	VS RE (%)	IWO (E)	IWO errors	IWO RE (%)	GSA (E)	GSA errors	GSA RE (%)	DE (E)	DE errors	DE RE (%)
1996	69.86	69.77	0.09	0.12	69.82	0.04	0.06	69.32	0.54	0.77	69.56	0.30	0.43	69.71	0.15	0.21
1997	73.78	72.43	1.35	1.82	72.48	1.30	1.76	71.90	1.88	2.55	72.30	1.48	2.00	72.32	1.46	1.99
1998	74.71	73.26	1.45	1.94	73.30	1.41	1.89	73.02	1.69	2.26	72.92	1.79	2.40	73.30	1.41	1.89
1999	76.77	74.33	2.44	3.17	74.37	2.40	3.12	74.10	2.67	3.48	73.74	3.03	3.95	74.18	2.59	3.37
2000	80.50	81.14	−0.64	−0.79	81.25	−0.75	−0.93	80.28	0.22	−0.28	80.79	−0.29	−0.37	80.71	−0.21	−0.27
2001	75.40	76.26	−0.86	−1.14	76.37	−0.97	−1.29	75.81	−0.41	−0.55	75.83	−0.43	−0.57	75.71	−0.31	−0.42
2002	78.33	79.56	−1.23	−1.57	79.65	−1.32	−1.68	79.08	−0.75	−0.96	79.32	−0.99	−1.27	79.13	−0.80	−1.02
2003	83.84	82.49	1.35	1.61	82.50	1.34	1.60	82.1	1.74	2.07	82.79	1.05	1.25	82.37	1.47	1.76
2004	87.82	87.14	0.68	0.77	87.07	0.75	0.85	86.53	1.29	1.47	88.41	−0.59	−0.68	87.19	0.63	0.72
2005	91.58	92.84	−1.26	−1.37	92.72	−1.14	−1.24	92.19	−0.61	−0.67	94.55	−2.97	−3.24	93.10	−1.52	−1.66

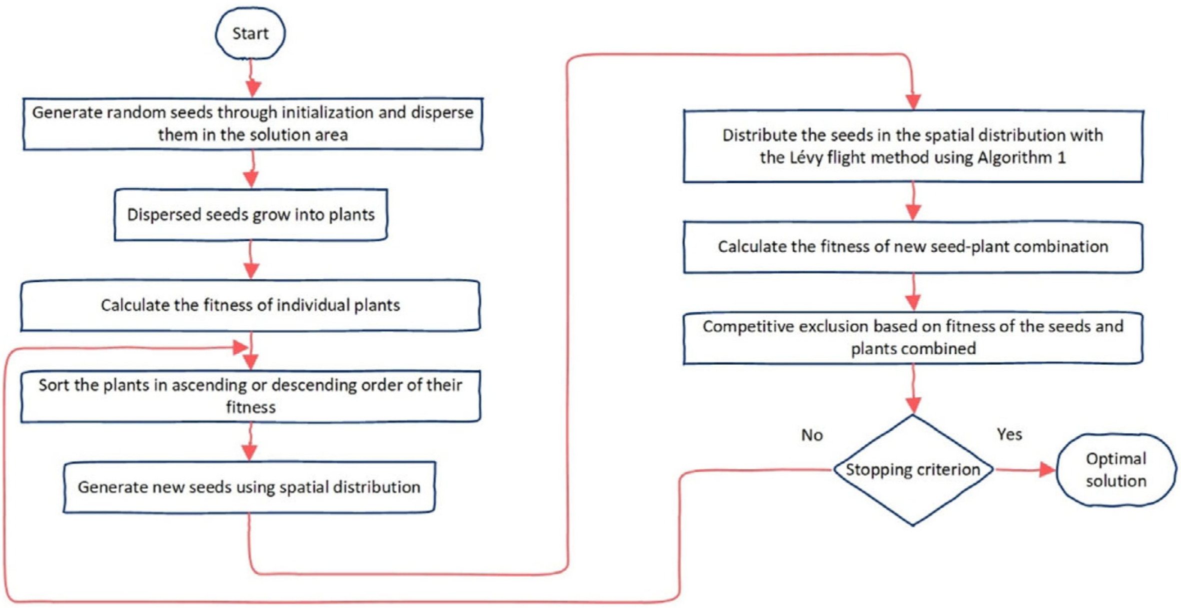

Fig. 1. Flowchart of LF-IWO.

Algorithm 1 Lévy Flight Method

for $i = 1$ *to* N **do**
    for $S = 1$ *to* S_{num} **do**
        Calculate $L_{stepsize}$ according to P^{iter} using Eq. (5);
        Distribute seeds according to the $L_{stepsize}$ using Eq. (3);
        Check if any individual goes beyond the value range and modify it;
    end
end
Return the new weed population.

Fig. 2. Pseudo-code of LF.

4. Experimental results

GDP, population, import and export data are important in the energy demand of a country [18]. Therefore, data between 1979 and 2011, available in the related reference, were used as input data (gross domestic product (GDP), population, import and export) [18]. These data were used for X_1, X_2, X_3 and X_4, respectively and a linear model was constructed in Eq. (6).

$$E_{linear} = w_1 + w_2X_1 + w_3X_2 + w_4X_3 + w_5X_4 \tag{6}$$

The weight and total error values obtained according to the linear model in Eq. (4) are shown in Table 1. The values in this table were obtained using data between 1979 and 2005. These data ware used to compare the results with the literature. Studies in literature such as Vortex search (VS) [29], IWO algorithm [30], gravity search algorithm (GSA) [30], differential evolution (DE) algorithm [18], hybrid approach (HAPE) based on particle swarm optimization and ant colony algorithm [16], artificial algae algorithm (AAA) [31], artificial bee colony with variable search strategies (ABCVSS) [32], bat algorithm (BA) [33], ACO [12], TSA [34] and PSO [15] methods, have

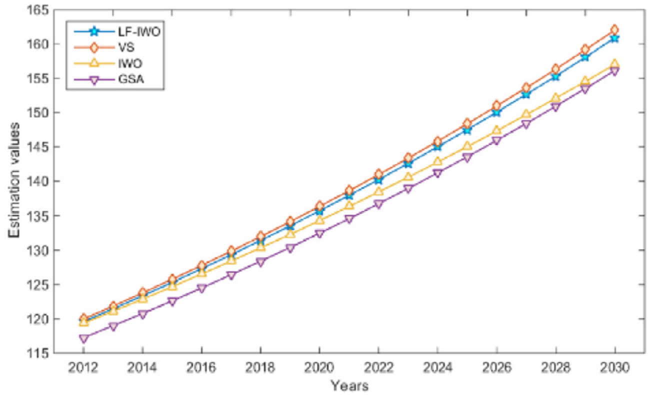

Fig. 3. Energy demand estimations in Turkey between 2012 and 2030 based on scenario 1.

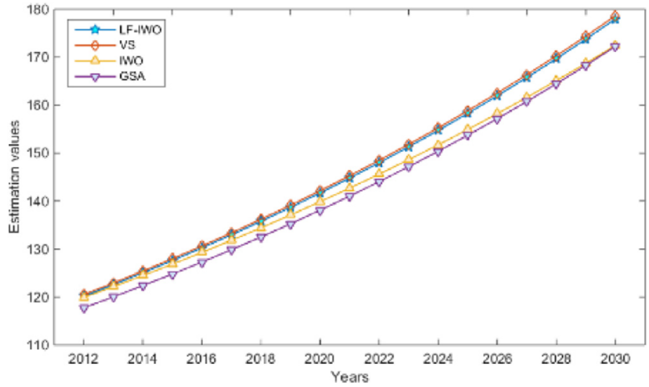

Fig. 4. Energy demand estimations in Turkey between 2012 and 2030 based on scenario 2.

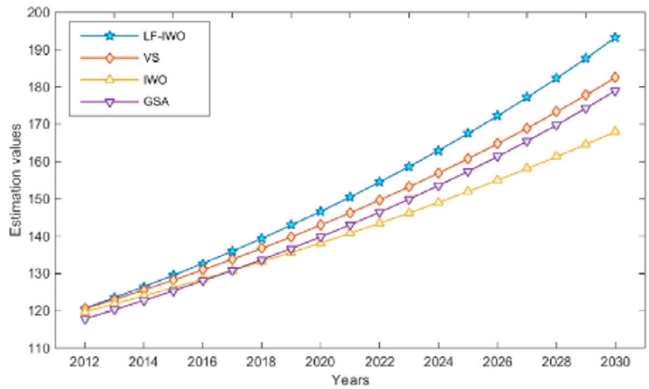

Fig. 5. Energy demand estimations in Turkey between 2012 and 2030 based on scenario 3.

predicted Turkey's energy demand. Weight and total error values obtained by using the data between 1979 and 2011 are shown in Table 3. In Table 1, the lowest error value achieved by the LF-IWO method is shown in bold.

Table 2 shows the estimated energy demand values of VS, IWO, GSA, and DE models between 1996 and 2005, the errors between the observed and estimated values and the relative error percentages. Moreover, the results obtained by the proposed LF-IWO model (PM) are also added to the table.

Table 3. The weight and total error values of the models developed for the data between 1979 and 2011.

Weight	LF-IWO	VS	IWO	GSA	DE
w1	−50.13206	−43.35375	−28.14013	−57.15262	−50.13452
w2	0.02389	0.02153	0.00582	0.02461	0.02389
w3	1.75759	1.63557	1.37398	1.89247	1.75763
w4	0.09961	0.09159	0.13009	0.08863	0.09997
w5	−0.03576	0.01120	0.05630	0.05971	−0.03635
Error	**152.64132**	169.05149	367.45717	180.36962	152.57090

Table 4. The Energy demand estimations of LF-IWO, VS, IWO, and GSA models between 2012 and 2030 based on scenarios 1, 2 and 3.

Year	OED	Scenario 1				Scenario 2				Scenario 3			
		LF-IWO	VS	IWO	GSA	LF-IWO	VS	IWO	GSA	LF-IWO	VS	IWO	GSA
2012	120.09	119.64	120.00	119.40	117.25	120.16	120.51	119.90	117.75	120.66	120.55	119.75	117.86
2013	120.29	121.49	121.88	121.13	119.01	122.57	122.93	122.15	120.02	123.50	123.02	121.84	120.27
2014	123.94	123.39	123.81	122.90	120.80	125.05	125.42	124.47	122.37	126.44	125.57	123.99	122.76
2015	129.30	125.32	125.78	124.70	122.64	127.60	127.99	126.85	124.79	129.49	128.22	126.20	125.35
2016	136.24	127.32	127.80	126.55	124.52	130.24	130.65	129.31	127.29	132.66	130.95	128.46	128.03
2017	N/A	129.35	129.87	128.43	126.45	132.97	133.39	131.83	129.86	135.95	133.79	130.79	130.81
2018	N/A	131.43	131.99	130.36	128.41	135.78	136.22	134.43	132.52	139.37	136.74	133.19	133.69
2019	N/A	133.57	134.16	132.32	130.43	138.68	139.14	137.10	135.26	142.93	139.79	135.65	136.69
2020	N/A	135.75	136.39	134.33	132.50	141.68	142.16	139.86	138.09	146.63	142.96	138.18	139.81
2021	N/A	138.00	138.67	136.39	134.61	144.78	145.28	142.69	141.02	150.47	146.25	140.79	143.05
2022	N/A	140.29	141.01	138.49	136.78	147.99	148.50	145.62	144.04	154.48	149.67	143.47	146.42
2023	N/A	142.65	143.42	140.64	139.00	151.31	151.83	148.63	147.16	158.65	153.23	146.23	149.92
2024	N/A	145.07	145.88	142.83	141.27	154.74	155.28	151.73	150.39	162.99	156.92	149.07	153.57
2025	N/A	147.54	148.41	145.08	143.61	158.28	158.85	154.93	153.73	167.51	160.77	151.99	157.38
2026	N/A	150.09	151.00	147.37	146.00	161.96	162.54	158.22	157.19	172.23	164.77	155.01	161.34
2027	N/A	152.70	153.66	149.72	148.45	165.76	166.36	161.62	160.77	177.15	168.94	158.11	165.48
2028	N/A	155.37	156.39	152.13	150.97	169.70	170.31	165.13	164.47	182.29	173.28	161.31	169.80
2029	N/A	158.12	159.20	154.58	153.55	173.78	174.41	168.74	168.31	187.65	177.80	164.61	174.30
2030	N/A	160.95	162.08	157.10	156.21	178.00	178.65	172.47	172.28	193.24	182.52	168.01	179.00

4.1. Forecasting Turkey's energy demand for the period between 2012 and 2030 using LF-IWO

The error rates of the LF-IWO algorithm obtained for the energy demand forecast of Turkey between 1979 and 2005 are shown in Tables 1 and 2. In this part of the study, the LF-IWO algorithm was used to estimate Turkey's energy demand between 2012 and 2030. For this purpose, the weight coefficients and error value of the forecast model were recalculated with the LF-IWO algorithm by using the data between 1979 and 2011. The results obtained using the LF-IWO algorithm are shown in Table 3 with the results of IWO and GSA models obtained by Koc et al. using the same input data [30] and the results of DE model obtained by Beskirli et al. [18]. The proposed LF-IWO algorithm had the same error value as the DE algorithm, which has been reported to have the lowest error value in the literature. The IWO algorithm, on the other hand, had the highest error value, making it the last in the ranking. While the IWO algorithm obtained the lowest error value, the LF-IWO algorithm achieved the success obtained by the DE algorithm. Thus, it was seen that the proposed LF-IWO algorithm became a more effective and robust algorithm.

To forecast the energy demand of Turkey between 2012 and 2030, first it is necessary to know input parameters of the forecast model, including GDP, population, import and export data between 2012 and 2030. Accordingly, input parameters for future energy forecast were created through three different scenarios used by Beskirli [18].

Scenario 1: between 2012 and 2030, annually, GDP increased by 4%, population by 0.5%, import by 2.5% and export by 3%. Scenario 2: between 2012 and 2030, annually, GDP increased by 5%, population by 0.6%, import by 3.5% and export by 3.5%. Scenario 3: between 2012 and 2030, annually, GDP increased by 6%, population by 0.6%, import by 3% and export by 3%.

Based on these scenarios, the amounts of energy demand in Turkey between 2012 and 2030 were predicted using LF-IWO, VS, IWO, and GSA models, as shown in Table 4. When Table 4 is analyzed, according to scenario 1, the VS model had the highest while the GSA model had the lowest energy demand forecast. The IWO model had energy demand forecasts close to the VS model in the first years while it had close forecast to the GSA model in the next years. On the other hand, LF-IWO obtained close values to the VS algorithm; however, any model could not obtain the observed energy demand values in scenario 1. Energy demand forecast values obtained according to scenario 2 were found to be quite similar to the case in scenario 1. According to scenario 3, GSA made the lowest energy demand forecast from 2012 to 2017 while it had higher forecast values than IWO after 2017. LF-IWO was found to be the model with the highest energy demand forecasts for all years.

On examining all scenarios, the LF-IWO was the only algorithm that could achieve the energy demand values observed for scenario 3. Figs. 3–5 show the graphs of LF-IWO, VS, IWO, and GSA algorithms according to scenarios.

As shown in Figs. 3 and 4, LF-IWO and VS algorithms obtained close estimation values to each other, while IWO and GSA algorithms could not achieve those values. Fig. 5 shows that the LF-IWO algorithm performed better than other algorithms and achieved an estimation value closer to the observed energy demand.

5. Conclusion

In this study, a new LF-IWO algorithm was proposed to forecast the energy demand of Turkey by improving the IWO algorithm with flight levy. A linear regression model was developed for the energy demand estimation problem with the LF-IWO algorithm. In the model, GDP, population, import, and export data were used as independent variables. A linear form model was created using data from two different time intervals, 1979–2005 and 1979–2011. The energy demand of Turkey between 2012 and 2030 was forecast by using the data between 1979 and 2011 through three different scenarios. Then the results were compared with the VS, IWO, GSA and DE prediction models in the literature. When the error values were compared according to the estimation models, it was seen that the LF-IWO algorithm had a lower error value than the other algorithms in the literature. It was seen that it achieved a good result especially compared to the basic IWO algorithm. As can be seen from the results, the IWO algorithm obtained inefficient results due to early convergence. In order to eliminate this problem, the IWO algorithm was developed with the levy flight method. Thus, the most important disadvantage of the IWO algorithm is eliminated by the levy flight method. When IWO and FL-IWO results are compared, the least error value was obtained with LF-IWO. Accordingly, the LF-IWO algorithm was able to obtain the closest value to the observed energy value for all three scenarios. Thus, due to the significant effect of the proposed method on the IWO algorithm, the stability and robustness of the algorithm have also increased. As a result, it has been determined that the LF-IWO algorithm performs a better estimation in energy demand estimation compared to other studies in the literature. In future studies, it is recommended to use the LF-IWO algorithm for different optimization problems. At the same time, it is recommended to compare the results of the study to be obtained by using different algorithms for the energy estimation problem and the results of this study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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