

^{1,3}Ismail KOC, ²Hasan KIVRAK, ³Ismail BABA OGLU

THE ESTIMATION OF THE ENERGY DEMAND IN TURKEY USING GREY WOLF OPTIMIZER ALGORITHM

^{1,3}Konya Technical University, Faculty of Engineering and Natural Sciences, Computer Engineering Department, Konya, TURKEY²Istanbul Technical University, Computer & Informatics Engineering Faculty, Computer Engineering Department, Konya, TURKEY

Abstract: Energy demand forecasting is an important issue whose solution is evaluated by policy makers in order to take the vital decisions that affect the economy of a country. In the last decade, several approaches including machine-learning techniques have been proposed to increase the success of this estimation. In this study, two different mathematical models are proposed to predict Turkey's energy demand by using the Grey Wolf Optimizer (GWO) algorithm. In the development of models, gross domestic product, population import and export are taken as parameters. Linear and quadratic mathematical models are used for energy demand forecast. From 1979 to 2011, 33 years of historical data are for training and testing phases of the models. The developed models are used to estimate energy demand of Turkey for a 29-year period from 2012 to 2040 in the three different possible scenarios. The GWO method is compared with other methods in the literature to prove its success for the energy demand problem. The results show that the proposed GWO method is more successful than the other methods, especially for the linear form.

Keywords: Energy demand, estimation, mathematical models, machine-learning techniques

1. INTRODUCTION

Energy as source of many things by means of growing role in the world economy and multi-purpose applications in production and consumption has a special importance. With the development of societies and the growing of economic activities, the demand for energy becomes important for the countries and their sectors [1]. Therefore, the idea of energy demand and energy policy remains an important issue. In the last twenty years, Turkey has become one of the world's fastest growing markets with young and growing population, rapid urbanization, strong economic fundamentals [2]. Energy demand is increasing with various social and economic developments all over the world. Similarly, the increasing population, urbanization and socio-economic development in Turkey has led to a rapid increase in energy demand in many sectors of the country [3].

Energy planning requires an analysis of past, present and future energy demands. Future energy demands are estimated by using energy demand models. Since governments can develop suitable strategic plans in consideration of realistic projection based on these models, modeling the energy demand constitutes an important phase of planning. For this reason, energy resources can be used more efficiently in various sectors [4].

In the last decade, several approaches including statistical techniques [5-8], machine-learning methods [9, 10], a novel hybrid approach based on particle swarm optimization and ant colony algorithm [11, 12], swarm intelligence [13], genetic algorithm [14], a hybrid approach of particle swarm optimization and artificial bee colony algorithm [15], differential evolution algorithm [16] have been proposed to predict Turkey's energy demand.

In this study, GWO algorithm, which is used in both linear and quadratic energy estimation, is preferred to predict the energy demand. Turkey's gross domestic product, population, import and export data for the years between 1979-2011 were used as training and test sets. For each proposed three different scenarios, the estimations for Turkey's primary energy demand are obtained. The estimates, which are observed to be very close to the amount of energy demand, were also compared with the primary energy demand forecasts made by the Ministry of Energy and Natural Resources (MENR). The remainder of this paper is organized as follows. Section 2 describes the Grey Wolf Optimizer (GWO) algorithm. Section 3 presents estimation of Turkey's energy demand using GWO. Section 4 shows the experimental results and we provide the conclusion of this paper in Section 5.

2. GREY WOLF OPTIMIZER

Gray Wolf Optimizer (GWO) is a swarm intelligence based algorithm inspired by the leadership and hunting behaviors of gray wolf groups [17]. These two features are mathematically represented as a powerful optimization method [18]. Grey wolves are classified as *alpha*, *beta*, *delta* and *omega* in relation to the social hierarchy. Alpha is the dominant species because the grey wolf group must comply with the rules of the *alpha*. The *beta* class represents secondary wolves that help *alpha* in the decision-making phase. *Omega* is the lowest gray wolf in rank. If any wolf does not belong to any of the species mentioned above, this wolf is called a *delta*. In the gray wolf algorithm, while the hunting is carried out by *alpha*, *beta* and *delta*, the search for prey is carried out by *omega* wolves to find a better solution [19]. The main stages of the GWO are respectively the stages of hunting, attacking prey and search for prey.

The flow chart of the GWO algorithm is given in Figure 1.

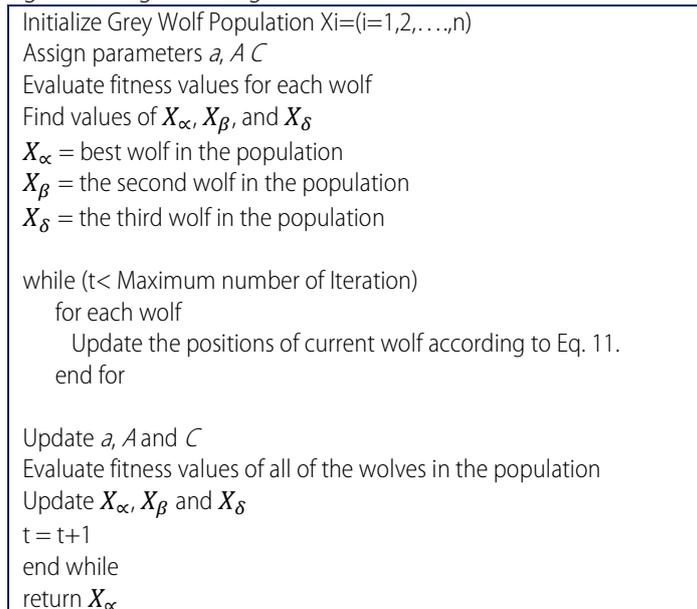


Figure 1. The flow chart of the GWO algorithm

3. ESTIMATION OF TURKEY'S ENERGY DEMAND USING GWO

In this section, linear and quadratic models have been proposed in order to perform estimation of Turkey's energy demand using GWO with the aid of Eq. (1) and (2). In the proposed model, four indicators which have been observed that one country has the most effect on the energy demand and which have been widely used in the literature were used to estimate the future of Turkey's energy demand [13, 20, 21]. These are gross domestic product, population, import and export, respectively. The linear form equation of four variables can be represented as in Eq. (1).

$$E_{linear} = w_1 + w_2X_1 + w_3X_2 + w_4X_3 + w_5X_4 \quad (1)$$

The quadratic form equation of four variables can be written as in Eq. (2).

$$E_{quadratic} = w_1 + w_2X_1 + w_3X_2 + w_4X_3 + w_5X_4 + w_6X_1X_2 + w_7X_1X_3 + w_8X_1X_4 + w_9X_2X_3 + w_{10}X_2X_4 + w_{11}X_3X_4 + w_{12}X_1X_1 + w_{13}X_2X_2 + w_{14}X_3X_3 + w_{15}X_4X_4 \quad (2)$$

X_1, X_2, X_3 and X_4 respectively represent the GDP, population, import and export values. The coefficients of the model represent a possible solution position for the proposed method. The proposed models optimize the coefficients (w_i) of the parameters (X_i) [22]. The aim is to determine the most suitable model for input data. The objective function used is shown in Eq. (3).

$$\min f(x) = \sum_{i=1}^N (E_i^{\text{observed}} - E_i^{\text{predicted}})^2 \quad (3)$$

In Eq. (3), N is the number of observations. E_i^{observed} is a i^{th} observed energy demand and $E_i^{\text{predicted}}$ is a i^{th} predicted energy demand.

4. EXPERIMENTAL RESULTS

Table 1 illustrates Turkey's energy demand, GDP, population, imports and exports data from 1979 until 2011. The data was obtained from Turkey Statistical Institute, Ministry of Energy and Natural Resources, and previous studies of [23, 24]. The data between the years 1979 and 2005 in Table 1 was used to generate linear and quadratic energy estimation models. GWO method was used for each of the two models and it was aimed to find the best model coefficient values. Ten independent runs of GWO algorithm were conducted and the best values were reported. We chose the maximum number of function evaluations (maxFES) and population size as 500.000 and 100, respectively. GWO method was also compared with different heuristic algorithms, such as ACO [12], PSO [13], HAPE [11] and DE [16] to validate its success.

The obtained coefficient values of the linear form using the GWO algorithm are shown in Table 2. Table 3 shows the comparisons of coefficients and relative errors in the linear form with different heuristic algorithms. As shown in Table 3, GWO method is the most successful than all other methods. While DE and HAPE algorithms have both approximately 41.70 relative errors, relative error of the proposed method is approximately 36.07 which have the best result than the others.

The obtained coefficient values of quadratic form using the GWO algorithm are shown in Table 4. Table 5 shows the comparisons of coefficients and relative errors in the quadratic form with different heuristic algorithms. GWO method was not very successful than all other methods, as seen in Table 5.

Table 1. Turkey's energy demand, GDP, population, import, export data

Year	Energy Demand (TWh)	GDP (\$ 10 ⁹)	Population (\$ 10 ⁶)	Import (\$ 10 ⁹)	Export (\$ 10 ⁹)
1979	30.71	82	45.53	5.07	2.26
1980	31.97	68	44.44	7.91	2.91
1981	32.05	72	45.54	8.93	4.7
1982	34.39	64	46.69	8.84	5.75
1983	35.7	60	47.86	9.24	5.73
1984	37.43	59	49.07	10.76	7.13
1985	39.4	67	50.31	11.34	7.95
1986	42.47	75	51.43	11.1	7.46
1987	46.88	86	52.56	14.16	10.19
1988	47.91	90	53.72	14.34	11.66
1989	50.71	108	54.89	15.79	11.62
1990	52.98	151	56.1	22.3	12.96
1991	54.27	150	57.19	21.05	13.59
1992	56.68	158	58.25	22.87	14.72
1993	60.26	179	59.32	29.43	15.35
1994	59.12	132	60.42	23.27	18.11
1995	63.68	170	61.53	35.71	21.64
1996	69.86	184	62.67	43.63	23.22
1997	73.78	192	63.82	48.56	26.26
1998	74.71	207	65	45.92	26.97
1999	76.77	187	66.43	40.67	26.59
2000	80.5	200	67.42	54.5	27.78
2001	75.4	146	68.37	41.4	31.33
2002	78.33	181	69.3	51.55	36.06
2003	83.84	239	70.23	69.34	47.25
2004	87.82	299	71.15	97.54	63.17
2005	91.58	361	72.97	116.77	73.48
2006	99.59	483	72.97	139.58	85.54
2007	107.63	531	70.59	170.06	107.27
2008	106.27	648	71.13	201.96	132.03
2009	106.14	730	73.23	140.93	102.14
2010	109.27	615	74.47	185.54	113.88
2011	114.48	731	74.72	240.84	134.91

Table 2. Coefficient values of the linear form

W1	W2	W3	W4	W5
-59.173	-0.00524	1.983764	0.3991	-0.50962

Table 3. Comparisons of coefficients and relative errors in linear form

Coeff.	GWO	DE	HAPE	ACO	PSO
w1	-59.1730	-55.8991	-55.9091	-51.3046	-55.9022
w2	-0.0052	0.0038	0.0038	0.0124	0.0021
w3	1.9838	1.9123	1.9126	1.8102	1.9126
w4	0.3991	0.3735	0.3734	0.3524	0.3431
w5	-0.5096	-0.4835	-0.4833	-0.4439	-0.4240
Hata	36.0767	41.7120	41.7029	45.7239	42.6139

Table 4. Coefficient values of the quadratic form

W1	W2	W3	W4	W5
-1.06343	-0.00161	0.05151	-0.01709	0.00002
W6	W7	W8	W9	W10
-0.00019	0.00295	0.00019	-0.00016	0.00392
W11	W12	W13	W14	W15
-0.01157	-0.00014	0.01495	-0.00066	-0.00084

Table 5. Comparisons of coefficients and relative errors in quadratic form

Coeff.	GWO	DE	HAPE	ACO	PSO
w1	-1.0634	-97.1458	-43.3096	-96.4418	-96.4408
w2	-0.0016	-0.4834	0.1039	-0.4820	-0.4820
w3	0.0515	4.7674	1.8110	4.7370	4.7370
w4	-0.0171	1.0991	-1.4778	1.0937	1.0937
w5	0.0000	-2.9212	1.1174	-2.8935	-2.9350
w6	-0.0002	0.0188	0.0025	0.0188	0.0188
w7	0.0030	0.0231	0.0112	0.0230	0.0230
w8	0.0002	-0.0256	-0.0074	-0.0255	-0.0255
w9	-0.0002	-0.0627	0.0121	-0.0625	-0.0625
w10	0.0039	0.1020	-0.0030	0.1014	0.1014
w11	-0.0116	0.0923	0.0158	0.0915	0.0915
w12	-0.0001	-0.0027	-0.0014	-0.0027	-0.0027
w13	0.0149	-0.0469	-0.0070	-0.0466	-0.0466
w14	-0.0007	-0.0390	-0.0170	-0.0389	-0.0387
w15	-0.0008	-0.0658	-0.0104	-0.0651	-0.0651
Hata	36.744	17.652	20.539	27.947	27.664

The results of energy demand estimation using the GWO method for two different models, GWO_L and GWO_Q, are shown in Table 6. It is observed that the estimated energy demands between the years 1996 and 2005 are very close to the actual energy demand values. The maximum relative error of GWO_L is -3.21%, while it is -3.10 for GWO_Q as seen in Table 6. Since both relative errors are negligible, we conclude that GWO_L and GWO_Q models give good accurate results for energy demand forecasts.

Table 6. The energy demand estimation of the proposed models between 1996 and 2005

Year	Observed Energy Demand MTOE	Estimated Energy Demand (MTOE)		Amount of Errors		Relative Errors (%)	
		Linear (GWO_L)	Quadratic (GWO_Q)	Linear (GWO_L)	Quadratic (GWO_Q)	Linear (GWO_L)	Quadratic (GWO_Q)
1996	69.86	69.76	69.32	0.44	-0.54	-0.14	-0.77
1997	73.78	72.42	72.23	0.19	-1.55	-1.84	-2.10
1998	74.71	73.27	75.05	-1.78	0.34	-1.93	0.45
1999	76.77	74.31	75.84	-1.53	-0.93	-3.21	-1.21
2000	80.50	81.12	80.90	0.22	0.40	0.77	0.49
2001	75.40	76.25	76.26	-0.01	0.86	1.13	1.13
2002	78.33	79.55	79.89	-0.34	1.56	1.56	1.99
2003	83.84	82.49	84.02	-1.53	0.18	-1.61	0.22
2004	87.82	87.14	85.10	2.04	-2.72	-0.77	-3.10
2005	91.58	92.85	93.17	-0.32	1.59	1.38	1.74

After demonstrating the success of the GWO algorithm for the linear model, 10 independent runs were conducted between years 1979 and 2011 using the linear form and the best model results were reported. Table 7 shows the coefficient values obtained for the linear form according to the data between the years 1979 and 2011. The calculated error is 152.648 based on the estimated coefficient parameters.

Table 8 presents the growth rates for three different scenarios using the updated data to estimate the future demand for energy in Turkey between the years of 2012-2040.

The results of energy demand forecast of the years between 2012 and 2040 using the GWO method with the obtained linear form coefficients in the scenarios are shown in Table 9. Table 9 shows the observed energy demand values between the years 2012 and 2015.

As seen in Table 9, the results that are very close to MTOE was obtained between 2012 and 2015 for 3 different scenarios. Although there is not much difference for three different scenarios, we can say that Scenario 1 predicts higher energy demand than Scenario 2 and Scenario 3. As a result, it is considered that the estimation results gathered from three different scenarios are reasonable for energy demand estimation.

5. CONCLUSION

Energy demand forecasting is an important issue in terms of both the economy and resources of countries for both developing countries and developed countries. In this study, Gray Wolf Optimizer (GWO) algorithm is used to predict Turkey's long-term energy demand. Considering the correlation between the increase in some economic indicators and energy consumption in Turkey, linear and quadratic mathematical formulations are proposed for energy demand forecast. Turkey's long-term energy demand was estimated from the years 2012 to 2040 in the three different scenarios with GWO method using the gross domestic product, population, import and export data. We have demonstrated the effectiveness of the GWO method for the energy demand problem through comparing with other methods proposed in the literature. The results show that the proposed GWO method is more successful than the other methods, especially for the linear formulation.

Note

This paper is based on the paper presented at INTERNATIONAL CONFERENCE ON APPLIED SCIENCES – ICAS 2018, organized by UNIVERSITY POLITEHNICA TIMISOARA, Faculty of Engineering Hunedoara (ROMANIA) and UNIVERSITY OF BANJA LUKA, Faculty of Mechanical Engineering (BOSNIA & HERZEGOVINA), in cooperation with the Academy of Romanian Scientists, Academy of Sciences Republic of Srpska, Academy of Technical Sciences of Romania – Timisoara Branch and General Association of Romanian Engineers – Hunedoara Branch, in Banja Luka, BOSNIA & HERZEGOVINA, 9 – 11 May 2018.

References

- [1] A. Azadeh, M. Saberi, S. Ghaderi, A. Gitiforouz, and V. Ebrahimipour, "Improved estimation of electricity demand function by integration of fuzzy system and data mining approach," *Energy Conversion and Management*, vol. 49, pp. 2165-2177, 2008.

Table 7. The coefficient values obtained for the linear form according to the data between the years 1979 and 2011

W1	W2	W3	W4	W5
-50.1722	0.023974	1.758293	0.101873	-0.03993

Table 8. Parameter values for different scenarios

Scenarios	The average growth rate of GDP (%)	Population growth rate (%)	Import growth rate (%)	Growth rate of exports (%)
Scenario 1	4.0	0.5	2.5	3.0
Scenario 2	4.0	0.5	2.5	3.5
Scenario 3	2.5	1.0	2.0	3.5

Table 9. Future projections of total energy demand in MTOE according to Scenarios 1, 2 and 3 for the proposed method

Year	Observed Energy Demand (MTOE)	Scenario -1	Scenario -2	Scenario -3
2012	120.09	119.74	119.66	119.94
2013	120.09	121.66	121.49	122.02
2014	123.94	123.63	123.35	124.13
2015	129,27	125.65	125.26	126.26
2016	N/A	127.74	127.21	128.43
2017	N/A	129.88	129.21	130.62
2018	N/A	132.09	131.25	132.85
2019	N/A	134.37	133.34	135.10
2020	N/A	136.72	135.48	137.38
2021	N/A	139.14	137.68	139.70
2022	N/A	141.64	139.92	142.04
2023	N/A	144.22	142.23	144.42
2024	N/A	146.88	144.59	146.82
2025	N/A	149.63	147.01	149.26
2026	N/A	152.48	149.49	151.73
2027	N/A	155.41	152.03	154.24
2028	N/A	158.45	154.64	156.78
2029	N/A	161.60	157.31	159.35
2030	N/A	164.85	160.06	161.95
2031	N/A	168.22	162.87	164.59
2032	N/A	171.71	165.77	167.27
2033	N/A	175.32	168.73	169.98
2034	N/A	179.06	171.78	172.72
2035	N/A	182.95	174.91	175.51
2036	N/A	186.97	178.13	178.33
2037	N/A	191.15	181.43	181.18
2038	N/A	195.49	184.83	184.08
2039	N/A	199.99	188.32	187.01
2040	N/A	204.67	191.91	189.98

- [2] O. E. Canyon and H. K. Öztürk, "Three different applications of genetic algorithm (GA) search techniques on oil demand estimation," *Energy conversion and management*, vol. 47, pp. 3138-3148, 2006.
- [3] M. Sonmez, A. P. Akgüngör, and S. Bektaş, "Estimating transportation energy demand in Turkey using the artificial bee colony algorithm," *Energy*, vol. 122, pp. 301-310, 2017.
- [4] A. Sadri, M. Ardehali, and K. Amirnekoeei, "General procedure for long-term energy-environmental planning for transportation sector of developing countries with limited data based on LEAP (long-range energy alternative planning) and EnergyPLAN," *Energy*, vol. 77, pp. 831-843, 2014.
- [5] V. Ş. Ediger and S. Akar, "ARIMA forecasting of primary energy demand by fuel in Turkey," *Energy Policy*, vol. 35, pp. 1701-1708, 2007.
- [6] V. Ş. Ediger and H. Tatlıdil, "Forecasting the primary energy demand in Turkey and analysis of cyclic patterns," *Energy Conversion and Management*, vol. 43, pp. 473-487, 2002.
- [7] Z. Yumurtaci and E. Asmaz, "Electric energy demand of Turkey for the year 2050," *Energy Sources*, vol. 26, pp. 1157-1164, 2004.
- [8] Z. Dilaver and L. C. Hunt, "Industrial electricity demand for Turkey: a structural time series analysis," *Energy Economics*, vol. 33, pp. 426-436, 2011.
- [9] A. Sözen and E. Arcaklioğlu, "Prospects for future projections of the basic energy sources in Turkey," *Energy Sources, Part B*, vol. 2, pp. 183-201, 2007.
- [10] M. Kankal, A. Akpınar, M. İ. Kömürçü, and T. Ş. Özşahin, "Modeling and forecasting of Turkey's energy consumption using socio-economic and demographic variables," *Applied Energy*, vol. 88, pp. 1927-1939, 2011.
- [11] M. S. Kıran, E. Özceylan, M. Gündüz, and T. Paksoy, "A novel hybrid approach based on particle swarm optimization and ant colony algorithm to forecast energy demand of Turkey," *Energy conversion and management*, vol. 53, pp. 75-83, 2012.
- [12] M. D. Toksarı, "Ant colony optimization approach to estimate energy demand of Turkey," *Energy Policy*, vol. 35, pp. 3984-3990, 2007.
- [13] A. Ünler, "Improvement of energy demand forecasts using swarm intelligence: The case of Turkey with projections to 2025," *Energy Policy*, vol. 36, pp. 1937-1944, 2008.
- [14] H. Ceylan and H. K. Ozturk, "Estimating energy demand of Turkey based on economic indicators using genetic algorithm approach," *Energy Conversion and Management*, vol. 45, pp. 2525-2537, 2004.
- [15] M. S. Kıran and M. Gündüz, "A recombination-based hybridization of particle swarm optimization and artificial bee colony algorithm for continuous optimization problems," *Applied Soft Computing*, vol. 13, pp. 2188-2203, 2013.
- [16] M. Beskirlı, H. Haklı, and H. Kodaz, "The energy demand estimation for Turkey using differential evolution algorithm," *Sādhanā*, vol. 42, pp. 1705-1715, 2017.
- [17] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Advances in engineering software*, vol. 69, pp. 46-61, 2014.
- [18] W. Long, J. Jiao, X. Liang, and M. Tang, "Inspired grey wolf optimizer for solving large-scale function optimization problems," *Applied Mathematical Modelling*, vol. 60, pp. 112-126, 2018.
- [19] A. K. Tripathi, K. Sharma, and M. Bala, "A Novel Clustering Method Using Enhanced Grey Wolf Optimizer and MapReduce," *Big Data Research*, 2018.
- [20] M. D. Toksarı, "Estimating the net electricity energy generation and demand using the ant colony optimization approach: case of Turkey," *Energy Policy*, vol. 37, pp. 1181-1187, 2009.
- [21] M. S. Kıran, E. Özceylan, M. Gündüz, and T. Paksoy, "Swarm intelligence approaches to estimate electricity energy demand in Turkey," *Knowledge-Based Systems*, vol. 36, pp. 93-103, 2012.
- [22] S. Gulcu and H. Kodaz, "The estimation of the electricity energy demand using particle swarm optimization algorithm: A case study of Turkey," *Procedia computer science*, vol. 111, pp. 64-70, 2017.
- [23] Y. M. Bulut and Z. Yıldız, "Comparing energy demand estimation using various statistical methods: the case of Turkey," *Gazi University Journal of Science*, vol. 29, pp. 237-244, 2016.
- [24] NS. National Statistics, (in Turkish) <http://www.tuik.gov.tr> 2016.



ISSN 1584 - 2665 (printed version); ISSN 2601 - 2332 (online); ISSN-L 1584 - 2665

copyright © University POLITEHNICA Timisoara, Faculty of Engineering Hunedoara,

5, Revolutiei, 331128, Hunedoara, ROMANIA

<http://annals.fih.upt.ro>