KSÜ Mühendislik Bilimleri Dergisi, 28(1), 2025
Araştırma Makalesi

KSU J Eng Sci, 28(1), 2025
Research Article

Kahramanmaras Sutcu Imam University
Journal of Engineering Sciences

Geliş Tarihi : 07.11.2024
Kabul Tarihi :31.01.2025

Received Date : 07.11.2024
Accepted Date :31.01.2025

FORECASTING ENERGY DEMAND IN TURKEY USING DIFFERENT METAHEURISTIC METHODS: A COMPARATIVE STUDY

TÜRKİYE'DE ENERJİ TALEBİNİN FARKLI METASEZGİSEL YÖNTEMLER KULLANILARAK TAHMİNİ: KARŞILAŞTIRMALI BİR ÇALIŞMA

Taner SEVMİŞ [1] (ORCID: 0000-0003-0034-4252)
Rasim ÇEKİK [1*] (ORCID: 0000-0002-7820-413X)

[1] Şırnak Üniversitesi, Bilgisayar Mühendisliği Bölümü, Şırnak, Türkiye

*Sorumlu Yazar / Corresponding Author: Rasim ÇEKİK, rasimcekik@sirnak.edu.tr

ABSTRACT

Energy demand forecasting plays a crucial role in shaping energy policies, particularly for countries like Turkey that experience rapid industrialization and urbanization. Accurately predicting energy demand helps to ensure energy supply security and to guide strategic investments, especially in transitioning towards renewable energy sources. This study explores the use of modern metaheuristic optimization methods to forecast Turkey's energy demand up to the year 2035, focusing on the effectiveness of various techniques in addressing this complex, multi-dimensional problem. The dataset used spans from 1979 to 2011 and includes economic and demographic indicators such as GDP, population, imports, and exports, which are key drivers of energy demand. Several metaheuristic algorithms, including The African Vultures Optimization Algorithm (AVOA), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), and Dynamic Bayesian Optimization (DBO), were applied to this dataset. A comparative analysis of these methods demonstrated that AVOA, GWO, DBO, and other similar approaches yielded the most accurate predictions, with minimum total error rates. The analysis revealed that the AVOA method outperformed other methods in terms of accuracy and computational efficiency by obtaining the lowest total error of 0.2391 and relative error percentage of 0.3565. The study highlights the significant role metaheuristic approaches play in improving the accuracy of energy demand forecasts and informs future policy decisions by identifying critical factors affecting Turkey’s energy consumption patterns. The findings are expected to contribute to more effective long-term energy planning and the development of sustainable energy policies.

Keywords: Energy demand, Turkey, metaheuristic, optimization

ÖZET

Enerji talebi tahmini, özellikle hızlı sanayileşme ve kentleşme yaşayan Türkiye gibi ülkelerde enerji politikalarının şekillendirilmesinde kritik bir rol oynamaktadır. Enerji talebinin doğru bir şekilde tahmin edilmesi, enerji arz güvenliğinin sağlanmasına ve yenilenebilir enerji kaynaklarına geçişte stratejik yatırımların yönlendirilmesine yardımcı olur. Bu çalışma, Türkiye'nin 2035 yılına kadar olan enerji talebini tahmin etmek amacıyla modern metasezgisel optimizasyon yöntemlerinin kullanımını araştırmakta ve bu karmaşık, çok boyutlu problemi ele almadaki etkinliklerini incelemektedir. Çalışmada, 1979-2011 yıllarını kapsayan ve GSYH, nüfus, ithalat ve ihracat gibi enerji talebinin temel belirleyicilerini içeren bir veri seti kullanılmıştır. Bu veri seti üzerinde Afrika Akbabaları Optimizasyon Algoritması (AVOA), Gri Kurt Optimizasyonu (GWO), Balina Optimizasyon Algoritması (WOA) ve Dinamik Bayes Optimizasyonu (DBO) gibi çeşitli metasezgisel algoritmalar uygulanmıştır. Karşılaştırmalı analiz sonuçları, AVOA, GWO, DBO ve benzeri yaklaşımların en düşük toplam hata oranlarıyla en doğru tahminleri sağladığını göstermektedir. Analizler, AVOA metodunun 0,2391 ile en düşük toplam hatayı ve 0,3565 bağıl hata yüzdesini elde ederek doğruluk ve hesaplama verimliliği açısından diğer yöntemlerden daha iyi performans gösterdiğini ortaya koymuştur. Çalışma, enerji talebi tahminlerinde metasezgisel yaklaşımların önemli bir rol oynadığını vurgulamakta ve Türkiye’nin enerji tüketim eğilimlerini etkileyen kritik faktörleri belirleyerek

ToCite: SEVMİŞ, T., & ÇEKİK, R., (2025). FORECASTING ENERGY DEMAND IN TURKEY USING DIFFERENT METAHEURISTIC METHODS: A COMPARATIVE STUDY. *Kahramanmaras Sutcu Imam University Journal of Engineering Sciences*, 28(1), 441-459.

gelecekteki politika kararlarına ışık tutmaktadır. Bulgular, uzun vadeli enerji planlamasının daha etkili hale getirilmesine ve sürdürülebilir enerji politikalarının geliştirilmesine katkı sağlamayı amaçlamaktadır.

Anahtar Kelimeler: Enerji talebi, Türkiye, metasezgisel, optimizasyon

INTRODUCTION

Energy demand is directly related to economic growth, demographic changes, and the social structure of countries, and it is shaped by the influence of various complex factors. Population growth, urbanization, technological progress, and improvements in living standards are the main factors driving increased energy consumption. In developing countries, rapid population growth and economic development lead to significant increases in energy demand, while in developed countries, technology-based production processes in the industrial and service sectors play a decisive role in energy consumption. In this context, in developing countries such as Turkey, energy demand is continuously increasing alongside urbanization and industrialization processes. Not only is the amount of energy demand changing, but so is the diversity of energy sources. While interest in renewable energy sources is increasing in line with sustainable development goals, the share of fossil fuels in the energy portfolio tends to decrease. However, this transition process occurs at different speeds depending on countries' infrastructure capacities and energy supply security policies. Turkey is accelerating the transition from fossil fuels to renewable resources to meet its energy needs, prioritizing investments in solar, wind, hydroelectric, and nuclear energy. According to World Energy Outlook, global energy demand will continue to rise until 2030 (Agency, 2009; Bilgen, Kaygusuz, and Sari, 2004). The growth rate of energy demand in developing countries is higher than in developed countries. Turkey's young population, rapid urbanization, and industrialization are gradually increasing the country's energy demand, which poses challenges for energy supply security. Therefore, accurately forecasting energy demand and making strategic plans accordingly are fundamental elements of energy policies (Sonmez, Akgüngör, and Bektaş, 2017).

The use of modern methods in energy demand forecasting is of great importance for maintaining the balance between energy supply and demand, as well as achieving high accuracy in long-term planning. In Turkey, official energy demand forecasts have been conducted by institutions such as the Ministry of Energy and Natural Resources, the Turkish Statistical Institute, and the State Planning Organization since 1984 (Ediger and Tatlıdil, 2002). However, the literature on this subject presents various approaches that have been developed and applied to forecast energy demand. Initially, statistical methods were preferred, but over time, more advanced techniques such as artificial neural networks and metaheuristic optimization techniques have emerged in energy demand forecasting. Metaheuristic optimization methods offer effective solutions for complex and multi-dimensional energy demand problems. The problem-independent nature of these methods makes them easily adaptable to various challenges, such as energy demand forecasting. Particularly in Turkey, the use of modern metaheuristic algorithms to accurately predict energy demand plays a strategic role in ensuring the balance between energy supply and demand. Energy demand forecasting is essential for balancing energy supply and demand and achieving sustainable development goals.

This study focuses on the critical application of metaheuristic methods to improve forecasting accuracy for Turkey’s energy demand. The main objectives are to evaluate the effectiveness of various modern optimization techniques, identify key influencing factors, and provide actionable insights for sustainable energy policy planning. For example, the transition to renewable energy sources in Turkey highlights the importance of accurate forecasting methods. Moreover, this study aims to analyze the performance of different metaheuristic optimization approaches in forecasting Turkey's energy demand up to the year 2030. By conducting a comparative evaluation of several recently proposed metaheuristic methods, critical parameters that contribute to the accurate prediction of energy demand have been identified. The study is based on energy demand data provided by the Ministry of Energy and Natural Resources (MENR) and the Turkish Statistical Institute (TÜİK), covering the period from 1979 to 2011 (Erdogdu, 2007; Koç, Nureddın, and Kahramanlı, 2018). This dataset serves as a comprehensive resource for analyzing past trends in energy consumption and projecting future scenarios. Various metaheuristic approaches were applied to this dataset to test the accuracy and effectiveness of the forecasting models (Bulut and Yıldız, 2016; Kaur, Awasthi, Sangal, and Dhiman, 2020). The methods included in this study are widely used techniques in optimization problems, yielding successful results in solving multi-dimensional and complex issues. These approaches offer significant advantages in terms of flexibility and accuracy in the modeling process for energy demand forecasting. The results obtained highlight which methods are more effective in energy forecasting and which parameters play a critical role in this process, thereby providing valuable insights to inform future energy policies.

The remainder of this paper is organized as follows: Section 2 offers a comprehensive review of related work. Section 3 discusses existing metaheuristic approaches. Section 4 presents the experimental results. Finally, Section 5 provides conclusions and discusses the implications of the findings.

RELATED WORKS

This section provides a comprehensive review of previous works in energy demand forecasting using metaheuristic techniques, including applications of Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and the Grey Wolf Optimizer (GWO). Comparative analysis of these methods demonstrates their respective strengths and applicability to specific forecasting challenges.

Energy demand forecasting is a critical topic in energy management and planning, essential for balancing energy production and consumption. In addition to traditional methods, the use of metaheuristic optimization techniques has gained significant prominence in this field in recent years. This section reviews key studies from existing literature on the application of metaheuristic methods in energy demand forecasting (Özdemir and Dörterler, 2022; Özdemir, Dörterler, and Aydın, 2022).

Tiris (2005) presents significant findings on Turkey's energy demand forecasts. The study projects that Turkey's annual energy demand will increase by 1.7% between 2002 and 2030. Based on 2012 data, Turkey's total primary energy demand was recorded as 121 MTEP, with the majority of this demand being met by fossil fuels. Turkey meets 70% of its energy demand through imports, a situation that raises concerns regarding energy security. The author emphasizes the importance of accurately forecasting energy demand to mitigate potential issues that may arise during the development and industrialization process. Additionally, various studies demonstrate the need for employing different methods to accurately forecast Turkey's energy demand. References (Dilaver and Hunt, 2011; Ediger and Akar, 2007; Kankal, Akpınar, Kömürcü, and Özşahin, 2011; Yumurtaci and Asmaz, 2004) discuss the use of statistical techniques, while references (Biçer, 2017; Es, Kalender Öksüz, and Hamzacebi, 2014; Sözen, Arcaklioğlu, and Özkaymak, 2005) provide examples of artificial neural networks techniques being applied to energy demand forecasting. References (Kıran, Özceylan, Gündüz, and Paksoy, 2012; Salcedo-Sanz, Muñoz-Bulnes, Portilla-Figueras, and Del Ser, 2015; Sánchez-Oro, Duarte, and Salcedo-Sanz, 2016; Uguz, Hakli, and Baykan, 2015) highlight the use of heuristic techniques, particularly in engineering applications, noting that population-based heuristic algorithms can provide quick solutions through multi-point procedures. Moreover, several modern methods have been proposed in this field. One of them is Genetic Algorithms (GA), introduced by Holland (1992), which is based on a population-driven approach and optimizes solutions through evolutionary processes. Dorigo (2007), inspired by the natural behavior of ant colonies, developed the Ant Colony Optimization (ACO) algorithm, which demonstrates effective performance, particularly in combinatorial optimization problems.

Kennedy and Eberhart (1995) developed Particle Swarm Optimization (PSO), an algorithm that models the social behaviors of swarms to search for solutions. This algorithm is widely used in energy demand forecasting due to its ability to provide quick solutions to complex problems with a low number of parameters.

(Corne et al., 1999; Kunkle et al., 2019) addressed high-dimensional, non-linear, and multi-objective optimization problems, emphasizing their importance in various industries, such as manufacturing, economics, healthcare, and transportation. The authors pointed out that traditional optimization methods fail to meet the complexity of these problems, leading to the broader application of metaheuristic algorithms.

Beheshti and Shamsuddin (2013) noted that nature-inspired metaheuristic algorithms find widespread application across various domains. The authors demonstrated that algorithms based on biological behaviors are particularly effective in solving problems with multiple extremum features.

Agarwal and Kumar (2022) conducted a comprehensive review of the Bat Algorithm (BA) and discussed its use in biological applications and optimization problems. Similarly, (Kar, 2016) evaluated the general principles, development processes, and application areas of biologically inspired algorithms.

Ezugwu et al. (2021) explored the impact of metaheuristic algorithms, particularly on clustering algorithms, and presented trends and advances in the field through a systematic review and bibliometric analysis. Such studies contribute to the growing use of metaheuristic algorithms in energy demand forecasting.

Finally, (Guo, Tang, Niu, and Lee, 2021) conducted a bibliometric review of the Bacterial Foraging Optimization (BFO) algorithm, offering an in-depth analysis of its information structures, research collaborations, and application areas. The study highlights the potential of such algorithms in energy demand forecasting.

Table 1. Characteristics of Commonly Employed Metaheuristic Methods

Article	Method	Population Based	Global Optimisation	Local Optimisation	Fast Convergence	Parameter Sensitivity	Multi-objective Optimisation	Energy Data Utilisation	Description
(Karaboga and Basturk, 2008)	Artificial Bee Colony (ABC)	✓	✓	✓	✓	✓	✓	✓	The artificial bee colony-based algorithm optimizes by direct interaction of the population.
(Guo et al., 2021; Passino, 2012)	Bacterial Foraging Optimization (BFO)	✓	✓	✓	✓	✓	✕	✓	It performs optimization by simulating bacterial movement and feeding processes.
(Agarwal and Kumar, 2022; Yang and He, 2013)	Bat Algorithm (BA)	✓	✓	✓	✓	✓	✕	✓	Based on the bat echolocation principle, it provides fast and flexible analyses.
(Kennedy and Eberhart, 1995)	Particle Swarm Optimization (PSO)	✓	✓	✕	✓	✓	✓	✓	It is based on a social interaction model that optimizes solutions through the movement of particles.
(Sarzaeim, Bozorg-Haddad, and Chu, 2018)	Teaching-Learning-Based Optimization (TLBO)	✓	✓	✓	✓	✕	✓	✓	A parameter-free optimization method based on a learning and teaching process.
(Yang and Slowik, 2020)	Firefly Algorithm (FA)	✓	✓	✓	✓	✓	✕	✓	Optimizes the attractiveness of fireflies according to their light intensity.
(Feoktistov, 2006)	Differential Evolution (DE)	✓	✓	✓	✓	✓	✓	✓	It optimizes by mutation and crossover between different solutions.
(Bertsimas and Tsitsiklis, 1993)	Simulated Annealing (SA)	✕	✓	✓	✕	✓	✕	✓	It seeks global optimization with temperature decrease but has slow convergence.
(Holland, 1992)	Genetic Algorithms (GA)	✓	✓	✓	✓	✓	✓	✓	Based on evolutionary processes, it generates multiple solutions through populations.
(Gendreau, 2003)	Tabu Search (TS)	✕	✓	✓	✕	✓	✕	✓	Guided local search algorithm with memory structures.
(Dorigo, 2007)	Ant Colony Optimization (ACO)	✓	✓	✓	✓	✓	✕	✓	It is based on the discovery of solutions by swarms of ants leaving a trail.
(Resende and Ribeiro, 2016)	GRASP	✓	✓	✓	✓	✓	✕	✓	It uses short-time refinement and a randomized heuristic search strategy.
(Wilson, Pallavi, Ramachandran, Chinnasamy, and Sowmiya, 2022)	Memetic Algorithms (MA)	✓	✓	✓	✓	✓	✓	✓	Combines local research with genetic algorithms; population co-operative resolution.

A comprehensive review by Li et al. (2024) addressed the historical development and fundamental principles of metaheuristic optimization methods. The authors categorized metaheuristic methods and emphasized their ability to enhance problem-solving capabilities. In particular, the applications of popular metaheuristic methods such as

Artificial Bee Colony (ABC), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO) in energy demand forecasting were detailed. The study also compared the performance of these methods and discussed which scenarios they might be more effective for. ABC, for instance, draws inspiration from natural systems and finds solutions based on the interactions between individuals, while GA offers population-based approaches, and PSO optimizes solutions through social interactions. The effectiveness of these methods in energy demand forecasting has been supported by experiments on real-world datasets.

Martí, Sevaux, and Sörensen (2024) examined the applications of next-generation metaheuristic methods in the energy sector. The authors assessed the potential of metaheuristic algorithms to improve energy efficiency, presenting a comparative performance analysis of both classical and innovative hybrid methods. Particular attention was given to the effectiveness of Tabu Search (TS) and Ant Colony Optimization (ACO) in energy demand forecasting. The findings showed ACO's ability to find optimal paths while exploring the solution space, and TS's use of memory structures to optimize solutions based on previously discovered solutions. The authors concluded that these methods play a crucial role in improving the accuracy of energy demand forecasting.

In another comprehensive review, Martín-Santamaría, López-Ibáñez, Stützle, and Colmenar (2024) explored the development of metaheuristic approaches and their application in various fields. The study underscored the problem-independent nature of metaheuristic algorithms and their ability to guide the development of problem-specific heuristic optimization techniques. The authors provided examples of how metaheuristic approaches can be applied to large-scale energy systems and summarized the key contributions from literature. The study also highlighted the strengths and weaknesses of metaheuristic methods, offering recommendations to guide future research in this area. Table 1 presents the comparative characteristics of some commonly used metaheuristics.

In conclusion, while the studies show the effectiveness of metaheuristics in energy demand forecasting, they also suggest that these techniques should be investigated more comprehensively in future research. In particular, combinations of different metaheuristic algorithms and the development of new approaches can contribute to better results in energy management. Moreover, it is important to continuously update and optimize the algorithms considering the current data sets and changing energy dynamics. In this context, the benefits and application potential of metaheuristic optimization techniques in energy demand forecasting have been further reinforced by important studies in the literature. These studies clearly demonstrate the contributions of metaheuristics in achieving energy efficiency and sustainability goals.

METAHEURISTIC METHODS

Metaheuristic algorithms have emerged as a crucial tool for solving complex optimization problems. These nature-inspired methods possess the capability to effectively address high-dimensional and multi-objective problems (Akter et al., 2024; Güven, Yörükeren, Tag-Eldin, and Samy, 2023; Pamuk, 2024). In this section, commonly used metaheuristic approaches in experimental studies. After giving detailed information about AVOA, GWO and BWOA methods, a summary information table is presented for the others.

African Vultures Optimization Algorithm (AVOA)

The African Vultures Optimization Algorithm (AVOA) is a novel metaheuristic algorithm inspired by the behavior of African vultures during their search for food (Abdollahzadeh, Gharehchopogh, and Mirjalili, 2021). The algorithm simulates the vultures' foraging strategies, navigation, and interactions with each other to solve complex global optimization problems. AVOA is designed to balance between exploration (searching new solutions) and exploitation (refining known solutions) by mimicking vultures' ability to navigate large areas and compete for limited resources.

AVOA was tested on 36 benchmark functions and several engineering design problems, and it demonstrated superior performance compared to other algorithms like Genetic Algorithm (GA), Whale Optimization Algorithm (WOA), and Grey Wolf Optimizer (GWO). The performance was evaluated based on various criteria such as the average solution quality, best and worst solutions, and convergence speed.

- Vulture Movement Equations: The vultures' movement is based on their proximity to the best solutions found so far. Vultures move towards the best vulture using the following equations:

$$P(i+1) = R(i) - D(i)xF \tag{1}$$

where, $P(i+1)$ is the position of the vulture in the next iteration and $R(i)$ is the current best solution. $D(i) = |X * R(i) - P(i)$ represents the distance between the vulture and the best solution and F is the satiation factor of the vultures.

- Satiation Factor F: The algorithm transitions between exploration and exploitation based on the vultures' "satiation" levels. The satiation factor F is modeled as:

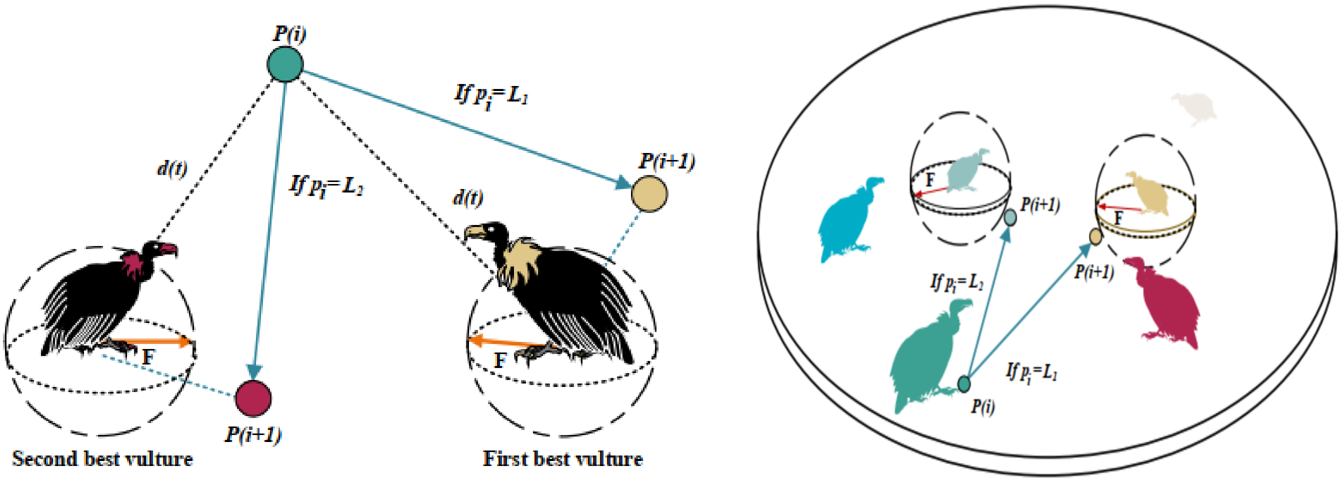
$$F = (2 * rand1 + 1) * z * \left(1 - \frac{iteration}{\max iteration}\right) + t \quad (2)$$

where, $rand1$ is a random number between 0 and 1, z is a random number between -1 and 1, t is a disturbance term that helps balance exploration and exploitation.

- Levy Flight Model: The vultures use Levy flights to enhance their exploration capabilities, especially when searching for new solutions. The Levy flight is modeled as:

$$LF(x) = 0.01 * \frac{\mu * \sigma}{|\upsilon|^{1/\beta}} \quad (3)$$

where, μ and υ are random numbers, β is a constant (usually 1.5), σ is a scaling factor based on β.



(a) (b)

Figure 1. (a) Example of Overall Vectors in the case of Competition for Food, (b) Example of Overall Vectors in the case of Aggressive Competition for Food (Abdollahzadeh et al., 2021)

Grey Wolf Optimizer (GWO)

The Grey Wolf Optimizer (GWO) algorithm is a metaheuristic optimization algorithm inspired by the social hierarchy and hunting behavior of grey wolves (Mirjalili, Mirjalili, and Lewis, 2014). The primary inspiration behind GWO is the leadership structure and hunting strategies exhibited by grey wolves. GWO models three main social roles: Alpha (α), Beta (β), and Delta (δ) wolves, which represent the best solutions in the optimization process, while Omega (ω) wolves represent the remaining solutions.

- **Social Hierarchy**: The alpha, beta, and delta wolves represent the top solutions, and the rest of the omega wolves position themselves according to these leaders.

- **Encircling the Prey**: Wolves update their positions based on the positions of the alpha, beta, and delta wolves as they surround the prey.

$$\vec{D} = |\vec{C}\vec{X}_p(t) - \vec{X}(t)| \tag{4}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}\vec{D}| \tag{5}$$

Here, t represents the current iteration, while $\vec{A}$ and $\vec{C}$ are coefficient vectors. $\vec{X}_p$ denotes the prey's position vector, and $\vec{X}$ represents the position vector of a grey wolf. The coefficient vectors $\vec{A}$ and $\vec{C}$ are determined as follows:

$$\vec{A} = 2\vec{a}\vec{r}_1 - \vec{a} \tag{6}$$

$$\vec{C} = \vec{r}_2 \tag{7}$$

where components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations and r_1, r_2 are random vectors in [0,1].

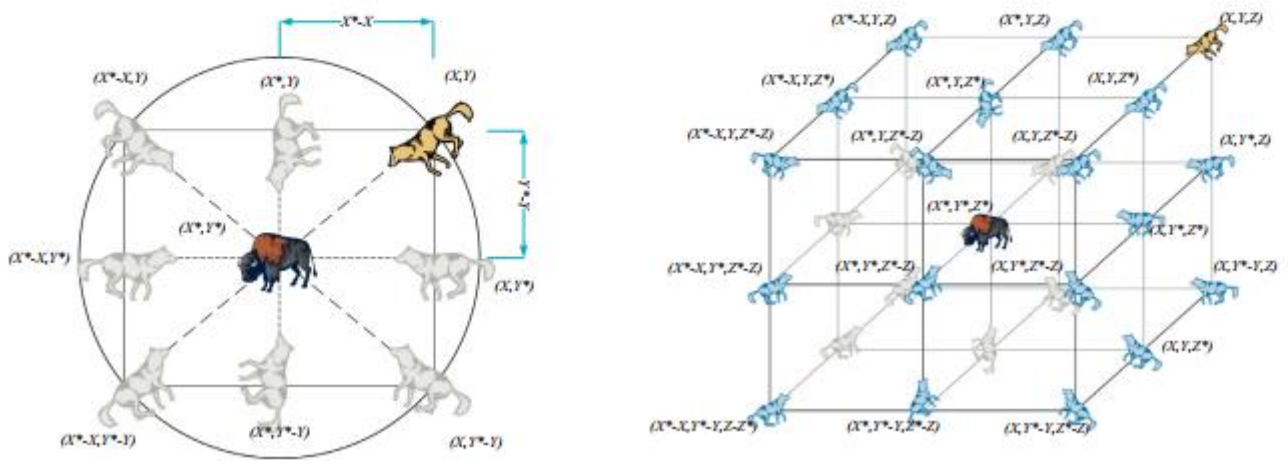


Figure 2. 2D and 3D Position Vectors and Their Possible Next Locations in GWO (Mirjalili et al., 2014).

- **Hunting**: Wolves follow the prey until the best solution is found, ultimately capturing the prey.

$$\vec{D}_\alpha = |\vec{C}_1\vec{X}_\alpha - \vec{X}|, \vec{D}_\beta = |\vec{C}_2\vec{X}_\beta - \vec{X}|, \vec{D}_\delta = |\vec{C}_3\vec{X}_\delta - \vec{X}| \tag{8}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1(\vec{D}_\alpha), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2(\vec{D}_\beta), \vec{X}_3 = \vec{X}_\delta - \vec{A}_3(\vec{D}_\delta) \tag{9}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{10}$$

The Black Widow Optimization Algorithm (BWOA)

The Black Widow Optimization Algorithm (BWOA) is a metaheuristic optimization method inspired by the biological behavior of the western black widow spider (Latrodectus hesperus) (Peña-Delgado et al., 2020). These spiders exhibit unique strategies in mating, movement, and cannibalistic behavior, which serve as the foundation for the algorithm's design.

- **Movement Strategy:** The movement of the black widow spider is modeled as both linear and spiral. The position of a new search agent ($\vec{x}_1(t+1)$) is updated based on the position of the best search agent from the previous iteration ($\vec{x}*(t)$) and the position of a randomly selected search agent ($\vec{x}_{r1}(t)$).

$$\vec{x}_1(t+1) = \begin{cases} \vec{x}*(t) - m\vec{x}_{r1}(t), & if\ rand() \leq 0.3, \\ \vec{x}*(t) - \cos(2\pi\beta)\,\vec{x}_1(t) & otherwise. \end{cases} \tag{11}$$

Here, m is a random coefficient selected from the interval [0.4, 0.9], and β is a random coefficient from the interval [-1.0, 1.0].

Pheromone Strategy: Pheromones play a critical role in the mating behavior of black widow spiders. Well-fed females produce higher pheromone levels, making them more attractive to males. The pheromone rate is calculated as follows:

$$pheromone(i) = \frac{fitness_{max} - fitness(i)}{fitness_{max} - fitness_{min}} \tag{12}$$

Where, $fitness_{max}$ and $fitness_{min}$ represent the highest and lowest fitness values in the current generation, respectively, while $fitness(i)$ denotes the fitness value of the ith search agent.

Female spiders with low pheromone levels are considered dangerous due to cannibalistic behavior and are thus replaced in the population:

$$\vec{x}_i(t) = \vec{x} * (t) + \frac{1}{2}\left[\vec{x}_{r_1}(t) - (-1)^{\sigma} * \vec{x}_{r_2}(t)\right] \tag{13}$$

In this equation, σ is a binary number randomly chosen from {0, 1}, and r_1 and r_2 are two different search agents selected randomly.

Time Complexity: The time complexity of the algorithm is defined as O(tMax ∗ nSp ∗ f), where tMax is the maximum number of iterations, nSp is the population size (number of spiders), and f is the computational complexity of the objective function being optimized.

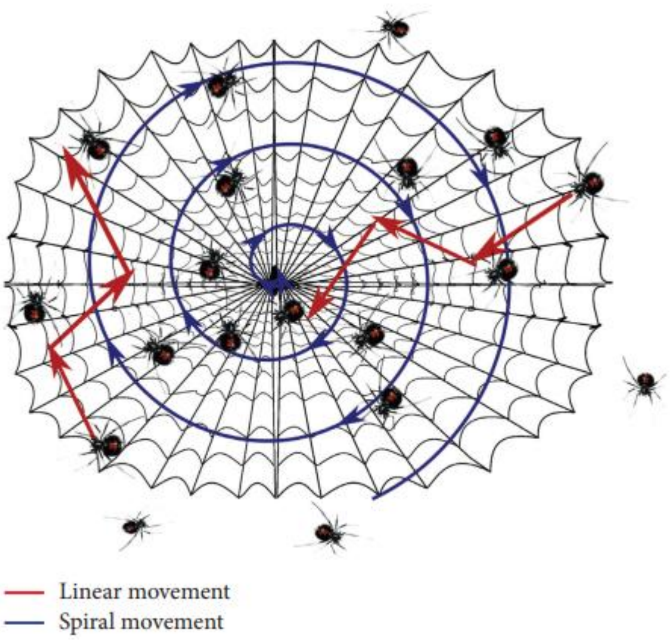


Figure 3. Typical Spider Movement within the Web (Peña-Delgado et al., 2020)

Information regarding the other methods used in experimental studies, aside from those previously discussed, is presented in Table 2. This table summarizes the inspiration sources, key features, and application areas of the methods. It provides a comprehensive comparison of all the methods included in the experiments, offering a broad overview of how each one is applied and utilized in different optimization problems.

EXPERIMENTAL WORKS

In this section, detailed information about the dataset used in the experimental studies is presented. First, the structure, sources, and characteristics of the dataset are explained to clarify the scope of the data forming the foundation of the study. Then, the results obtained by the existing metaheuristic approaches on this dataset are analyzed in detail, and the performance of each method is compared based on various criteria. In this way, the effectiveness of different methods and their success on the dataset are evaluated.

Table 2. Summary of Additional Metaheuristic Methods Used in Experimental Studies

Method	Inspiration Source	Key Features	Application Areas
Arithmetic Optimization Algorithm (AOA)	Mathematical Operators	Based on Addition, Subtraction, Multiplication, and Division; balances exploration and exploitation (Abualigah, Diabat, Mirjalili, Abd Elaziz, and Gandomi, 2021).	Engineering design and various optimization problems.
Blood-Sucking Leech Optimizer (BSLO)	Blood-Sucking Leech Behavior	Five hunting strategies, strong exploration and exploitation capability; can be integrated with ANN (Bai et al., 2024).	Engineering design and melting electrospinning fiber diameter prediction.
Chernobyl Disaster Optimizer (CDO)	Chernobyl Nuclear Explosion	Based on radiation spread; balances exploration and exploitation (Shehadeh, 2023).	Global optimization problems and engineering design.
Dung Beetle Optimizer (DBO)	Dung Beetle Behavior	Fast convergence rate and solution accuracy; applicable to engineering designs (Xue and Shen, 2023).	Complex engineering designs and global optimization problems.
Hybrid Firefly and Particle Swarm Optimization (HFPSO)	Firefly and Particle Swarm Optimization	Combines strengths of firefly and PSO; improved balance of exploration and exploitation (Aydilek, 2018).	Engineering and computationally expensive problems.
Nutcracker Optimizer (NOA)	Clark's Nutcracker Birds	Based on seasonal food-searching strategies, it provides superior performance in engineering designs (Abdel-Basset, Mohamed, Jameel, and Abouhawwash, 2023).	Complex optimization problems and engineering design.
Sinh Cosh Optimizer (SCHO)	Sinh and Cosh Mathematical Functions	Two phases of exploration and exploitation; bounded search strategy (Bai et al., 2023).	Complex optimization problems and engineering designs
Whale Optimization Algorithm (WOA)	Whale Hunting Strategy	Based on bubble-net hunting strategy; superior exploration and exploitation capabilities (Mirjalili and Lewis, 2016).	Structural optimization and engineering designs.
Aquila Optimizer (AO)	Aquila's Prey-Catching Behavior	Optimization procedures include soaring, contour flight, low flight, and swooping attacks; strong exploration and exploitation balance (Abualigah, Yousri, et al., 2021).	Tested on 23 functions, CEC2017 and CEC2019 test functions, and seven real-world engineering problems
Golden Sine Algorithm (Gold-SA)	Sine Function & Golden Section	Math-based algorithm inspired by sine; narrows search space using the golden section, leading to faster convergence with fewer parameters (Tanyildizi and Demir, 2017).	General optimization problems, shows superior performance compared to other population-based methods
Reptile Search Algorithm (RSA)	Crocodile Hunting Behavior	Incorporates unique encircling (high/belly walking) and hunting (coordination/cooperation) behaviors; demonstrated superior performance in benchmark tests and real-world problems (Abualigah, Abd Elaziz, Sumari, Geem, and Gandomi, 2022).	Tested on 23 classical functions, CEC2017 and CEC2019 test functions, and seven real-world engineering problems, achieving better results compared to other algorithms.

Dataset

The analysis of Turkey's energy demand between 1979 and 2011 was conducted using data on imports, population, exports, and GDP. These data are presented in detail in Table 1 and are based on official statistics provided by the Turkish Statistical Institute (TÜİK) and the Ministry of Energy and Natural Resources (ETKB) (Koç et al., 2018). In the scope of the study, the effects of these economic and demographic factors on energy demand were observed, and the findings were evaluated within the framework of the energy supply and demand balance. Detailed information regarding the dataset is provided in Table 3.

Table 3 reveals that Turkey's economic values have continuously increased over the years, reflecting the country's development process. Moreover, based on the data derived from the table, a strong relationship between the rise in economic indicators and energy consumption can be observed. This indicates that economic growth progresses in parallel with the increase in energy demand, positioning energy consumption as a significant indicator of economic development. In this context, linear models have been employed in the study for energy demand forecasting. To accurately analyse the relationship between economic growth and energy demand, the linear models demonstrate how changes in energy consumption align with economic indicators.

Table 3. Turkey's Energy Demand, GDP, Population, Imports and Exports between 1979-2011

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

Model

Linear models have been employed in this study to predict how energy demand interacts with factors such as economic growth, population increase, and industrialization. The fundamental assumption of these models is that the increase in economic indicators is directly related to the increase in energy demand. Turkey's energy demand data for the period 1979-2011 are used. This data set includes the main determinants of energy demand such as Gross Domestic Product (GDP), population, imports and exports. The mathematical expression of the linear model used in the study is presented in Equation 14, and this model is structured to estimate the effects of economic indicators on energy demand.

$$E_{linear} = w_1 + w_2X_1 + w_3X_2 + w_4X_3 + w_5X_4 \tag{14}$$

The primary goal of energy demand forecasting is to determine the most suitable values in light of the available data. In Equation 14, X_1, X_2, X_3 and X_4 represent the Gross Domestic Product (GDP), population, imports, and exports, respectively. Based on these data, the weight values w_1, w_2, w_3, w_4 and w_5 are calculated to obtain the optimal energy demand prediction for specific years. The objective function used is shown in Equation 15, which plays a critical role in determining the optimal weights during the process of energy demand prediction.

$$\min \mathrm{f}(x) = \sum_{i=1}^{M} (E_i^{observed} - E_i^{predicted}) \tag{15}$$

In this case, $E_i^{observed}$ and $E_i^{predicted}$represent the actual and predicted values for the $i-th$ data point, respectively, and M denotes the total number of data points.

It is also worth noting this point. Evaluation metrics include Root Mean Square Error (RMSE), offering robust measures of forecasting accuracy.

Experimental Results and Analysis

In this section, the performance results of the different metaheuristic algorithms introduced in the previous sections are discussed in detail. These performance evaluations are presented in various tables and figures. Table 4 presents the total error and the weight coefficients obtained for optimal values through the methods for the years 1979-2000.

Tablo 4. Total Error Values and Weight Coefficients obtained by the Algorithms for the Years 1979-2000

	W_1	W_2	W_3	W_4	W_5	$minf(x)$
GWO	-32.1724	0.0316	1.3161	0.2138	0.2812	**23.0204**
WOA	-23.9307	0.0480	1.1117	-0.0182	0.7151	33.0276
NOA	-22.6343	0.0279	1.0985	0.1892	0.4671	41.8404
AO	-14.0644	0.0314	0.8984	0.0752	0.8511	31.1919
HFPSO	-32.1827	0.0315	1.3164	0.2115	0.2855	23.0224
AVOA	-32.1518	0.0316	1.3156	0.2136	0.2816	**23.0204**
DBO	-32.1824	0.0316	1.3163	0.2138	0.2808	**23.0204**
GoldSA	0.3618	0.0380	0.5725	0.0504	1.0635	44.5907
SCHO	-32.0998	0.0317	1.3143	0.2121	0.2848	23.0220
AOA	0.0193	0.0284	0.5798	-0.0561	1.3288	50.0386
BWOA	-32.1824	0.0316	1.3163	0.2138	0.2808	**23.0203**
BSLO	-32.1824	0.0316	1.3163	0.2138	0.2808	**23.0203**
CDO	0.1062	0.0355	0.5785	0.0739	1.0425	44.0240
RSA	-36.1380	0.0092	1.4315	0.3727	0.0448	35.3284

Table 4 presents a diverse set of approaches, including GWO, WOA, NOA, AO, HFPSO, AVOA, DBO, GoldSA, SCHO, AOA, BWOA, BSLO, CDO, and RSA. The fact that each algorithm finds different values for certain weights w_1, w_2, w_3, w_4 and w_5 reveals that different approaches can be used to provide solutions to Turkey's energy demand forecasting problem. The total error value (min f(x)) in the table is an important indicator of the solution quality of the algorithms, and smaller values indicate better solutions. In particular, the algorithms that reached the smallest relative error value of 23.0204-GWO, AVOA, DBO, BWOA and BSLO-performed the best for this problem. These algorithms were successful in minimizing the objective function, which shows their effectiveness. However, some algorithms such as GoldSA, AOA and CDO have larger relative error values compared to other methods. This may indicate that these algorithms are not suitable for this problem or that they may need different parameter settings to perform more effectively. In conclusion, the table presents the comparative performance of various algorithms and clearly shows which methods are more effective for forecasting Turkey's energy demand. However, although this table gives a general idea, a deeper analysis is needed. For this purpose, Table 5 show the estimated energy amounts for the 10 years between 1991 and 2000, the amount of error between the actual energy demand and the estimated energy amount and the relative error percentages according to the weights found by the algorithms (GWO, AVOA, DBO, BWOA and BSLO) which give the best results according to Table 4 and WOA which gives an average result in addition to them. The reason for choosing WOA is to make the details of the analysis more understandable by giving an algorithm that gives an average result along with the algorithms that give good results.

Table 5 presents remarkable results. When the table is analysed, it is seen that the AVOA algorithm exhibits the best performance in terms of prediction accuracy compared to other algorithms. Moreover, the algorithm was able to produce forecasts very close to the actual energy demand values. One of the main reasons why AVOA is so effective in the energy demand forecasting problem is its adaptability to this problem with low computational cost and its ability to work on the problem with high efficiency. In addition, the algorithm's reflexive search mechanisms enable more efficient exploration of the solution space by preventing it from falling into local minimum traps. The most important factor for AVOA to be effective in this problem is the preservation of population diversity by using F coefficient and randomisation techniques and balancing the search process with multiple strategies.

Table 5. Predicted Energy Values (P), Error Rates (E), and Relative Error Percentages (RE) of the Algorithms for the Years 1991-1995

Year		1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
OED		54.2700	56.6800	60.2600	59.1200	63.6800	69.8600	73.7800	74.7100	76.7700	80.5000
GWO	**P**	54.6417	56.8093	60.2536	59.4907	65.5045	69.2506	72.5976	76.2010	75.4121	80.5016
	E	0.3717	0.1293	-0.0064	0.3707	1.8245	-0.6094	-1.1824	1.4910	-1.3579	0.0016
	RE	0.6850	0.2282	0.0106	0.6270	2.8650	0.8724	1.6027	1.9958	1.7687	0.0020
WOA	**P**	54.8860	57.0548	59.4008	60.3274	65.3972	68.0185	71.4816	77.2847	76.9787	79.5002
	E	0.6160	0.3748	-0.8592	1.2074	1.7172	-1.8415	-2.2984	2.5747	0.2087	-0.9998
	RE	1.1350	0.6613	1.4257	2.0423	2.6966	2.6359	3.1153	3.4463	0.2718	1.2420
AVOA	**P**	**54.2700**	**56.6800**	**60.1641**	**59.1083**	**63.6713**	**69.8600**	**73.7800**	**74.7100**	**76.6523**	**80.4949**
	E	**0.000**	**0.000**	**-0.0959**	**-0.0117**	**-0.0087**	**0.000**	**0.000**	**0.000**	**-0.1177**	**-0.0051**
	RE	**0.002**	**0.002**	**0.1592**	**0.0198**	**0.0137**	**0.000**	**0.000**	**0.000**	**0.1534**	**0.0064**
DBO	**P**	4.6374	56.8049	60.2470	59.4882	65.5013	69.2459	72.5939	76.1982	75.4097	80.4955
	E	0.3674	0.1249	-0.0130	0.3682	1.8213	-0.6141	-1.1861	1.4882	-1.3603	-0.0045
	RE	0.6770	0.2203	0.0215	0.6228	2.8600	0.8790	1.6076	1.9920	1.7720	0.0056
BWOA	**P**	54.6394	56.8070	60.2506	59.4889	65.5023	69.2479	72.5952	76.1989	75.4103	80.4986
	E	0.3694	0.1270	-0.0094	0.3689	1.8223	-0.6121	-1.1848	1.4889	-1.3597	-0.0014
	RE	0.6807	0.2240	0.0156	0.6240	2.8617	0.8762	1.6059	1.9930	1.7712	0.0018
BSLO	**P**	54.6394	56.8070	60.2506	59.4889	65.5023	69.2479	72.5952	76.1989	75.4103	80.4986
	E	0.3694	0.1270	-0.0094	0.3689	1.8223	-0.6121	-1.1848	1.4889	-1.3597	-0.0014
	RE	0.6807	0.2240	0.0156	0.6240	2.8617	0.8762	1.6059	1.9930	1.7712	0.0018

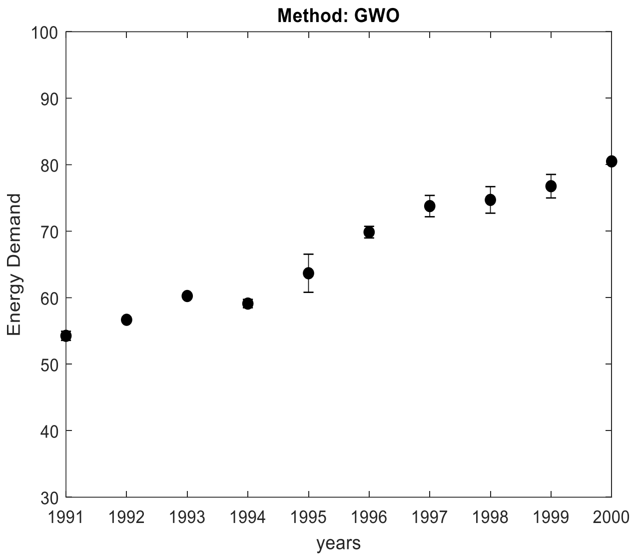
The total error amounts and relative error percentages of the algorithms are summarized in Table 6 in order to provide a more comprehensive comparison. This additional table provides an important reference point to analyze and compare the performance of different algorithms in more detail.

Table 6. Total Error Values and Total Relative Error Percentages obtained by the Algorithms for 1991-2000

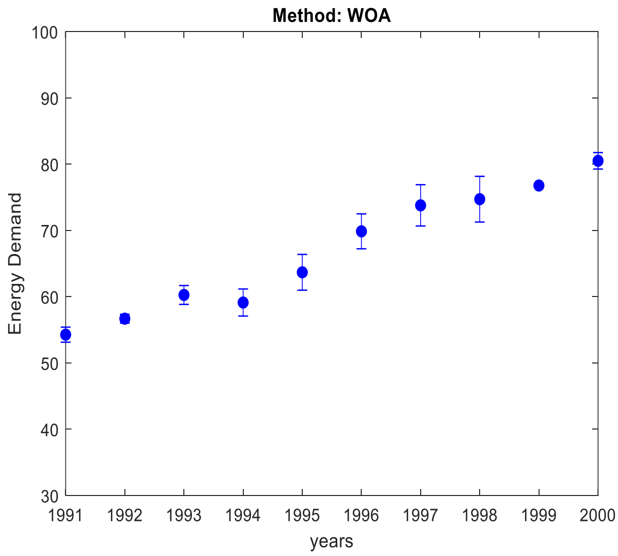
Method	Total Error	Total Relative Error (%)
GWO	7.3449	10.6574
WOA	12.6977	18.6722
AVOA	**0.2391**	**0.3565**
DBO	7.3480	10.6578
BWOA	7.3439	10.6541
BSLO	7.3439	10.6541

In Table 6, the total error and total relative error percentages are calculated as the sum of the absolute values of the results found by the algorithms. According to the table, the AVOA method's lowest 'Total Error' and 'Total Relative Error (%)' values indicate that it outperforms the other methods. This result suggests that the AVOA method yields predictions closer to the actual values. Additionally, the similar results of the DBO, BWOA, and BSLO methods suggest comparable performance among these approaches, while the higher error values of the WOA method suggest relatively lower accuracy compared to the others. To examine each method's annual performance in energy demand forecasting, data from Table 5 were used to create Figure 4, enabling an assessment of the reliability of the results and visualization of significant differences and error margins across methods.

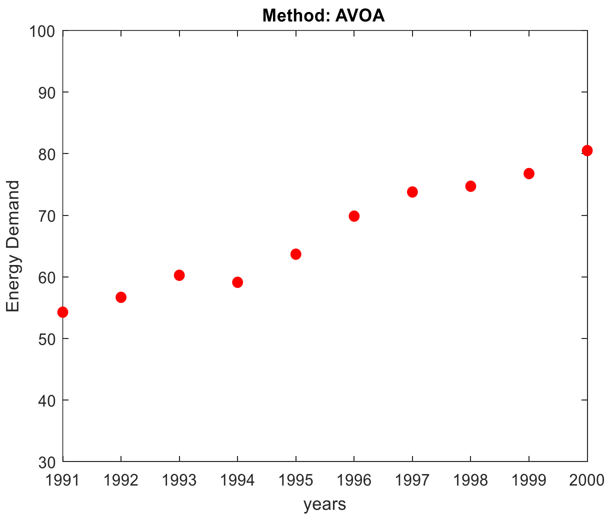
Upon examining Figure 1, it is evident that the AVOA method consistently yields the lowest error values across all years. In contrast, the GWO method exhibits fluctuating error values between 1995 and 1999, reaching a peak in 1995. The figure also indicates that the DBO, BWOA, and BSLO methods display similar behaviors. Meanwhile, the WOA method shows higher error values compared to the other methods, indicating a broader range of error values; notably, it peaked in 1998. Overall, the AVOA method provides stable results that are closer to the actual values, while the WOA method presents more erratic and higher errors. The other approaches, on the other hand, yield comparable and similar results.



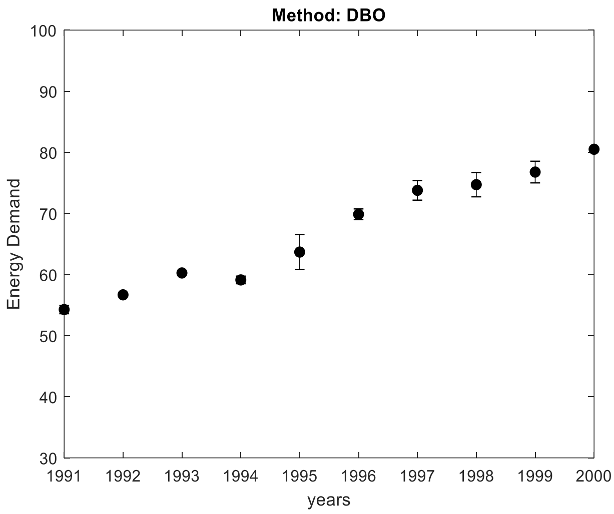
(a)



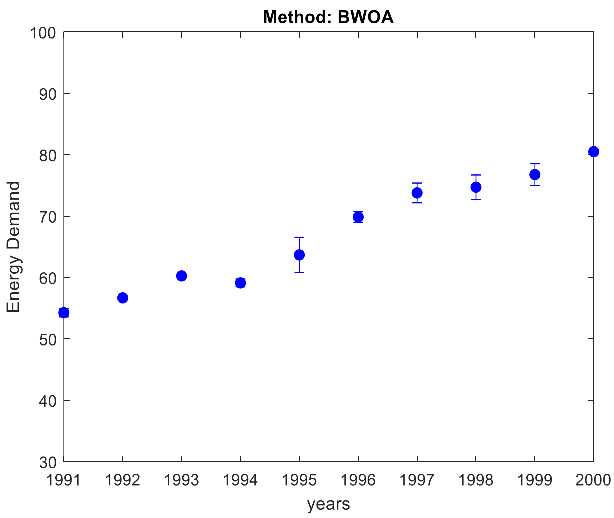
(b)



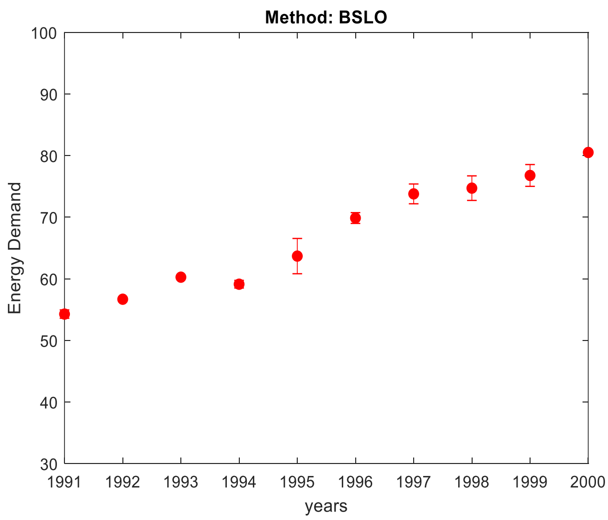
(c)



(d)



(e)



(f)

Figure 4. Error Values of Methods in Annual Energy Demand Forecasting (1991-2000)

Prediction of Turkey's Future Energy Demand for the Period 2012-2030: To enable the methods to predict Turkey's energy demand for the period 2012-2030, optimal coefficients were first determined using the complete data from 1979-2011. Accordingly, coefficient values that optimize the predictive performance of each method were calculated, and the results are presented in Table 7.

Table 7. Total Error Values and Weight Coefficients obtained by the Algorithms for the Years 1979-2011

	W_1	W_2	W_3	W_4	W_5	$minf(x)$
GWO	-64.6293	0.0476	2.0569	0.0011	-0.0895	134.3387
WOA	-57.9652	0.1023	1.8814	-0.1918	-0.0757	243.9200
AVOA	**-65.0584**	**0.0445**	**2.0682**	**0.0370**	**-0.1312**	**132.4312**
DBO	-65.0595	0.0455	2.0682	0.0372	-0.1322	132.5312
BWOA	-65.0593	0.0463	2.0682	0.0375	-0.1343	133.4312
BSLO	-65.1585	0.0453	2.0682	0.0372	-0.1331	132.6312

When examining Table 7, it is observed that AVOA yields better results compared to the other algorithms. Following this, future energy demand predictions were conducted based on the scenarios presented in Table 8, using the data from Table 7. These scenarios aim to evaluate the predictive performance of the methods under different conditions.

Table 8. Possible Scenarios for the Years 2012-2030

Data	Scenario I	Scenario II	Scenario III
Average GDP growth rate (%)	4.0	5.0	6.0
Population growth rate (%)	0.5	0.6	0.6
Growth rate of imports (%)	2.5	3.5	3.0
Growth rate of exports (%)	3	3.5	3.0

The scenarios presented in Table 8 were compiled from updated data by Koç et al. (2018). to forecast Turkey's energy demand for the period 2012-2030. The results obtained by the methods according to these scenarios are shared in two parts. In the first part, the methods' results for 2012-2020 are presented in tabular form, while the results for 2021-2030 are illustrated graphically. This structure aims to reveal the performance differences and trends of the methods across both periods in detail, allowing for a clear analysis of each method's reliability and accuracy over the long term.

The results obtained by the methods under Scenario I are presented in detail in Table 9 and Figure 5. This table and figure examine the energy demand forecasting performance of each method for the period 2012-2030, providing an in-depth analysis of variations across different years and conditions. Thus, the effectiveness and accuracy of each method used under Scenario I are evaluated from a comparative perspective. The same procedure was also performed for Scenario II and Scenario III.

When Table 9 and Figure 5 are analysed, it is seen that the methods have different error rates. According to Scenario 1, except for the WOA method, the other methods have generally displayed a more balanced performance and produced close results. In particular, the forecast values obtained for the years 2012-2015 are quite close to the probable actual values, indicating that the methods provide consistent results. However, the WOA method, unlike the other methods, exhibited a significant imbalance and showed significant deviations in some years, as clearly seen in Figure 1. This indicates that WOA provides more fluctuating and inconsistent performance compared to other methods. The results obtained by the methods under Scenario 2 are presented in Table 10 and Figure 6.

Table 9. Predicted Energy Demand Rates of the Methods according to Scenario 1 for the Years 2012-2020

	GET	GWO	WOA	AVOA	DBO	BWOA	BSLO
2012	120.0900	115.7065	105.5395	116.7947	117.4917	117.8998	117.1058
2013	120.2900	117.6107	107.9464	118.6532	119.3788	119.8051	118.9827
2014	123.9400	119.5677	110.4463	120.5608	121.3162	121.7614	120.9095
2015	129.2700	121.5795	113.0431	122.5195	123.3059	123.7709	122.8883
2016	N/A	123.6483	115.7413	124.5313	125.3499	125.8356	124.9209
2017	N/A	125.7763	118.5453	126.5981	127.4503	127.9575	127.0096
2018	N/A	127.9660	121.4600	128.7223	129.6094	130.1391	129.1565
2019	N/A	130.2198	124.4900	130.9059	131.8294	132.3825	131.3639
2020	N/A	132.5401	127.6407	133.1515	134.1128	134.6904	133.6342

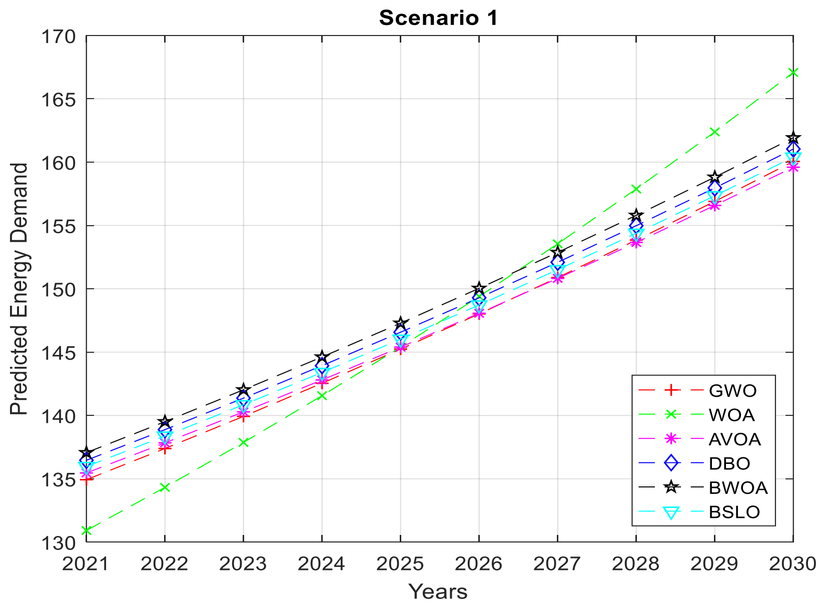


Figure 5. Predicted Energy Demand Rates of the Methods according to Scenario 1 for the Years 2021-2030

Tablo 10. Predicted energy demand rates of the methods according to Scenario 2 for the years 2012-2020

	GET	GWO	WOA	AVOA	DBO	BWOA	BSLO
2012	120.0900	114.2969	103.5968	115.4640	116.1406	116.5364	115.7625
2013	120.2900	116.6236	106.3281	117.7862	118.4981	118.9169	118.1078
2014	123.9400	119.0322	109.1892	120.1882	120.9371	121.3803	120.5343
2015	129.2700	121.5268	112.1876	122.6740	123.4619	123.9307	123.0458
2016	N/A	124.1117	115.3309	125.2476	126.0765	126.5724	125.6467
2017	N/A	126.7913	118.6273	127.9135	128.7854	129.3098	128.3412
2018	N/A	129.5706	122.0855	130.6761	131.5932	132.1478	131.1340
2019	N/A	132.4543	125.7146	133.5402	134.5049	135.0912	134.0300
2020	N/A	135.4478	129.5240	136.5108	137.5255	138.1453	137.0342

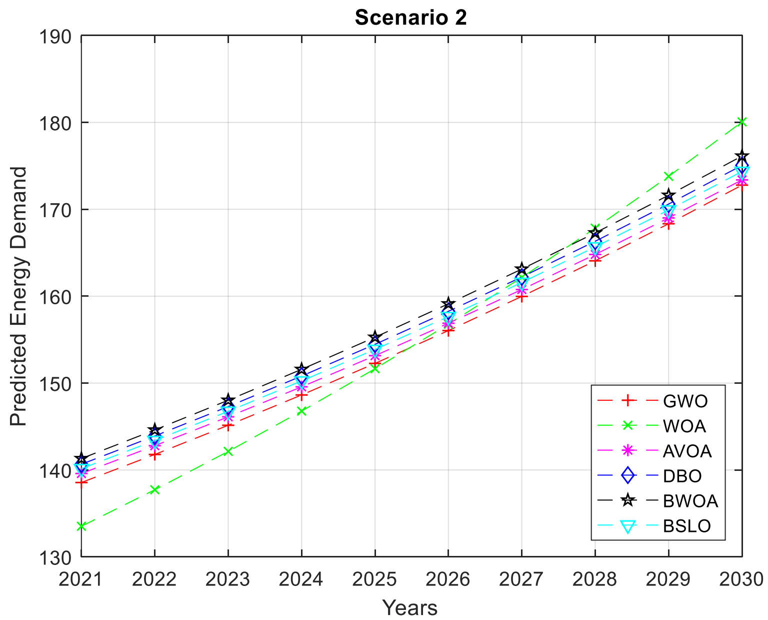


Figure 6. Predicted Energy Demand Rates for the Years 2021-2030 by Methods under Scenario II

Under Scenario II, results similar to those of Scenario I were obtained; however, it is observed that the methods generally provide higher energy demand forecasts. Notably, the WOA method offers the lowest predictions compared to other methods up until 2025, after which it begins to provide higher forecast values than its counterparts. This indicates a significant change and upward trend in the predictions made by the WOA method. On the other hand, the AVOA method displays a trajectory that closely aligns with the average of the other methods' forecast values, suggesting that it offers a more balanced and consistent predictive performance. This stability implies that AVOA could be a more reliable method for energy demand forecasting. The results obtained by the methods under Scenario 3 are presented in Table 11 and Figure 7.

Tablo 11. Predicted Energy Demand Rates of the Methods according to Scenario 3 for the Years 2012-2020

	GET	GWO	WOA	AVOA	DBO	BWOA	BSLO
2012	120.0900	114.7039	104.6267	115.8332	116.5176	116.9203	116.1386
2013	120.2900	117.4797	108.4884	118.5633	119.2915	119.7249	118.8994
2014	123.9400	120.3829	112.5882	121.4149	122.1897	122.6558	121.7839
2015	129.2700	123.4211	116.9418	124.3954	125.2195	125.7205	124.7993
2016	N/A	126.6026	121.5657	127.5124	128.3890	128.9271	127.9535
2017	N/A	129.9359	126.4776	130.7740	131.7062	132.2840	131.2549
2018	N/A	133.4302	131.6960	134.1889	135.1802	135.8002	134.7121
2019	N/A	137.0952	137.2410	137.7662	138.8203	139.4852	138.3345
2020	N/A	140.9413	143.1337	141.5157	142.6364	143.3492	142.1320

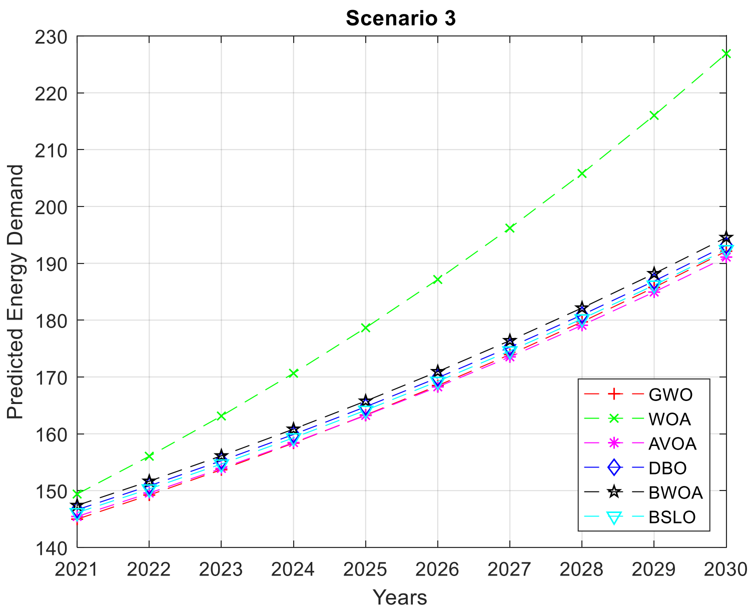


Figure 7. Predicted Energy Demand Rates for the years 2021-2030 by Methods under Scenario III

When examining Table 11 and Figure 7, it is evident that Scenario 3 presents the highest energy demand forecasts. In this scenario, the energy demand predictions from all methods are generally high. Notably, the WOA method stands out by providing significantly high forecast values starting from 2020. Conversely, the other methods exhibit a more balanced and stable performance, displaying similar behavior as in the previous scenarios.

Overall, the inference that can be drawn from all three scenarios is that AVOA provides forecasts close to the average throughout the years, while WOA presents low predictions for the initial eight years, followed by higher forecasts thereafter. Additionally, the other methods have also produced results that are balanced and consistent, similar to AVOA. This suggests that AVOA and other methods demonstrating similar behavior may be more reliable and stable in forecasting energy demand.

CONCLUSION AND DISCUSSIONS

This study investigates the effectiveness of modern metaheuristic optimization methods in forecasting Turkey's energy demand up to the year 2035. Accurate energy demand forecasts are critically important for shaping the country's energy policies. A comparative analysis using data from 1979 to 2011, which includes economic and demographic indicators, demonstrates that methods such as AVOA, GWO, and DBO provide the most accurate predictions with the lowest total error rates. Furthermore, the results indicate that the AVOA algorithm outperforms other methods in energy demand forecasting. Key findings indicate that AVOA achieved the highest accuracy, with results closely aligning with actual energy demand values. The algorithm's low computational cost, ability to maintain population diversity, and its capacity to explore the solution space more efficiently without getting trapped in local minimal are fundamental reasons for its success in this domain. Table 2 presents the relative performance of all methods, while Figure 3 visualizes annual error trends, emphasizing AVOA's consistency and reliability. Additionally, methods such as DBO, BWOA, and BSLO also exhibit similar performance, offering effective alternatives alongside AVOA for accurately predicting energy demand.

This study aims to identify the key factors influencing energy demand, contributing to the development of sustainable energy policies in Turkey. The findings provide valuable insights for future energy planning, helping to maintain the balance between energy supply and demand. Therefore, the use of modern metaheuristic methods is expected to enhance the reliability of energy demand forecasting in developing countries like Turkey, facilitating the more effective implementation of energy policies.

REFERENCES

Abdel-Basset, M., Mohamed, R., Jameel, M., & Abouhawwash, M. (2023). Nutcracker optimizer: A novel nature-inspired metaheuristic algorithm for global optimization and engineering design problems. *Knowledge-Based Systems*, *262*, 110248.

Abdollahzadeh, B., Gharehchopogh, F. S., & Mirjalili, S. (2021). African vultures optimization algorithm: A new nature-inspired metaheuristic algorithm for global optimization problems. *Computers & Industrial Engineering*, *158*, 107408.

Abualigah, L., Abd Elaziz, M., Sumari, P., Geem, Z. W., & Gandomi, A. H. (2022). Reptile Search Algorithm (RSA): A nature-inspired meta-heuristic optimizer. *Expert Systems with Applications*, *191*, 116158.

Abualigah, L., Diabat, A., Mirjalili, S., Abd Elaziz, M., & Gandomi, A. H. (2021). The arithmetic optimization algorithm. *Computer Methods in Applied Mechanics and Engineering*, *376*, 113609.

Abualigah, L., Yousri, D., Abd Elaziz, M., Ewees, A. A., Al-Qaness, M. A. A., & Gandomi, A. H. (2021). Aquila optimizer: a novel meta-heuristic optimization algorithm. *Computers & Industrial Engineering*, *157*, 107250.

Agarwal, T., & Kumar, V. (2022). A systematic review on bat algorithm: Theoretical foundation, variants, and applications. *Archives of Computational Methods in Engineering*, 1–30.

Agency, I. E. (2009). *World energy outlook*. OECD/IEA Paris.

Akter, A., Zafir, E. I., Dana, N. H., Joysoyal, R., Sarker, S. K., Li, L., … Kamwa, I. (2024). A review on microgrid optimization with meta-heuristic techniques: Scopes, trends and recommendation. *Energy Strategy Reviews*, *51*, 101298.

Aydilek, I. B. (2018). A hybrid firefly and particle swarm optimization algorithm for computationally expensive numerical problems. *Applied Soft Computing*, *66*, 232–249.

Bai, J., Li, Y., Zheng, M., Khatir, S., Benaissa, B., Abualigah, L., & Wahab, M. A. (2023). A sinh cosh optimizer. *Knowledge-Based Systems*, *282*, 111081.

Bai, J., Nguyen-Xuan, H., Atroshchenko, E., Kosec, G., Wang, L., & Wahab, M. A. (2024). Blood-sucking leech optimizer. *Advances in Engineering Software*, *195*, 103696.

Beheshti, Z., & Shamsuddin, S. M. H. (2013). A review of population-based meta-heuristic algorithms. *Int. j. Adv. Soft Comput. Appl*, *5*(1), 1–35.

Bertsimas, D., & Tsitsiklis, J. (1993). Simulated annealing. *Statistical Science*, *8*(1), 10–15.

Biçer, A. (2017). *Enerji talep tahminine yönelik program geliştirme ve bir bölge için uygulaması*.

Bilgen, S., Kaygusuz, K., & Sari, A. (2004). Renewable energy for a clean and sustainable future. *Energy Sources*, *26*(12), 1119–1129.

Bulut, Y. M., & Yıldız, Z. (2016). Comparing energy demand estimation using various statistical methods: the case of Turkey. *Gazi University Journal of Science*, *29*(2), 237–244.

Corne, D., Dorigo, M., Glover, F., Dasgupta, D., Moscato, P., Poli, R., & Price, K. V. (1999). *New ideas in optimization*. McGraw-Hill Ltd., UK.

Dilaver, Z., & Hunt, L. C. (2011). Industrial electricity demand for Turkey: a structural time series analysis. *Energy Economics*, *33*(3), 426–436.

Dorigo, M. (2007). Ant colony optimization. *Scholarpedia*, *2*(3), 1461.

Ediger, V. Ş., & Akar, S. (2007). ARIMA forecasting of primary energy demand by fuel in Turkey. *Energy Policy*, *35*(3), 1701–1708.

Ediger, V. Ş., & Tatlıdil, H. (2002). Forecasting the primary energy demand in Turkey and analysis of cyclic patterns. *Energy Conversion and Management*, *43*(4), 473–487.

Erdogdu, E. (2007). Electricity demand analysis using cointegration and ARIMA modelling: A case study of Turkey. *Energy Policy*, *35*(2), 1129–1146.

Es, H., KALENDER ÖKSÜZ, F., & Hamzacebi, C. (2014). Forecasting the net energy demand of Turkey by artificial neural networks. *Journal of the Faculty of Engineering and Architecture of Gazi University*, *29*(3).

Ezugwu, A. E., Shukla, A. K., Nath, R., Akinyelu, A. A., Agushaka, J. O., Chiroma, H., & Muhuri, P. K. (2021). Metaheuristics: a comprehensive overview and classification along with bibliometric analysis. *Artificial Intelligence Review*, *54*, 4237–4316.

Feoktistov, V. (2006). *Differential evolution*. Springer.

Gendreau, M. (2003). An introduction to tabu search. In *Handbook of metaheuristics* (pp. 37–54). Springer.

Guo, C., Tang, H., Niu, B., & Lee, C. B. P. (2021). A survey of bacterial foraging optimization. *Neurocomputing*, *452*, 728–746.

Güven, A. F., Yörükeren, N., Tag-Eldin, E., & Samy, M. M. (2023). Multi-objective optimization of an islanded green energy system utilizing sophisticated hybrid metaheuristic approach. *IEEE Access*.

Holland, J. H. (1992). Genetic algorithms. *Scientific American*, *267*(1), 66–73.

Kankal, M., Akpınar, A., Kömürcü, M. İ., & Özşahin, T. Ş. (2011). Modeling and forecasting of Turkey's energy consumption using socio-economic and demographic variables. *Applied Energy*, *88*(5), 1927–1939.

Kar, A. K. (2016). Bio inspired computing–a review of algorithms and scope of applications. *Expert Systems with Applications*, *59*, 20–32.

Karaboga, D., & Basturk, B. (2008). On the performance of artificial bee colony (ABC) algorithm. *Applied Soft Computing*, *8*(1), 687–697.

Kaur, S., Awasthi, L. K., Sangal, A. L., & Dhiman, G. (2020). Tunicate Swarm Algorithm: A new bio-inspired based metaheuristic paradigm for global optimization. *Engineering Applications of Artificial Intelligence*, *90*, 103541.

Kıran, M. S., Özceylan, E., Gündüz, M., & Paksoy, T. (2012). A novel hybrid approach based on particle swarm optimization and ant colony algorithm to forecast energy demand of Turkey. *Energy Conversion and Management*, *53*(1), 75–83.

Koç, İ., Nureddın, R., & Kahramanlı, H. (2018). Türkiye'de Enerji Talebini Tahmin Etmek İçin Doğrusal Form Kullanarak GSA (Yerçekimi Arama Algoritmasi) ve IWO (Yabani Ot Optimizasyon Algoritmasi) Tekniklerinin Uygulanmasi. *Selçuk Üniversitesi Mühendislik, Bilim ve Teknoloji Dergisi*, *6*(4), 529–543.

Kunkle, B. W., Grenier-Boley, B., Sims, R., Bis, J. C., Damotte, V., Naj, A. C., … Amlie-Wolf, A. (2019). Genetic meta-analysis of diagnosed Alzheimer's disease identifies new risk loci and implicates Aβ, tau, immunity and lipid processing. *Nature Genetics*, *51*(3), 414–430.

Li, G., Zhang, T., Tsai, C.-Y., Yao, L., Lu, Y., & Tang, J. (2024). Review of the metaheuristic algorithms in applications: Visual analysis based on bibliometrics (1994–2023). *Expert Systems with Applications*, 124857.

Martí, R., Sevaux, M., & Sörensen, K. (2024). 50 years of metaheuristics. *European Journal of Operational Research*.

Martín-Santamaría, R., López-Ibáñez, M., Stützle, T., & Colmenar, J. M. (2024). On the automatic generation of metaheuristic algorithms for combinatorial optimization problems. *European Journal of Operational Research*.

Mirjalili, S., & Lewis, A. (2016). The whale optimization algorithm. *Advances in Engineering Software*, *95*, 51–67.

Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey wolf optimizer. *Advances in Engineering Software*, *69*, 46–61.

Özdemir, D., & Dörterler, S. (2022). An adaptive search equation-based artificial bee colony algorithm for transportation energy demand forecasting. *Turkish Journal of Electrical Engineering and Computer Sciences*, *30*(4), 1251–1268.

Özdemir, D., Dörterler, S., & Aydın, D. (2022). A new modified artificial bee colony algorithm for energy demand forecasting problem. *Neural Computing and Applications*, *34*(20), 17455–17471.

Pamuk, N. (2024). Techno-economic feasibility analysis of grid configuration sizing for hybrid renewable energy system in Turkey using different optimization techniques. *Ain Shams Engineering Journal*, *15*(3), 102474.

Passino, K. M. (2012). Bacterial foraging optimization. In *Innovations and Developments of Swarm Intelligence Applications* (pp. 219–234). IGI Global.

Peña-Delgado, A. F., Peraza-Vázquez, H., Almazán-Covarrubias, J. H., Torres Cruz, N., García-Vite, P. M., Morales-Cepeda, A. B., & Ramirez-Arredondo, J. M. (2020). A Novel Bio-Inspired Algorithm Applied to Selective Harmonic Elimination in a Three-Phase Eleven-Level Inverter. *Mathematical Problems in Engineering*, *2020*(1), 8856040.

RC, K. J. E. (1995). Particle swarm optimization. *Proc IEEE Int Conf Neural Networks*, *4*, 1942–1948.

Resende, M. G. C., & Ribeiro, C. C. (2016). *Optimization by GRASP*. Springer.

Salcedo-Sanz, S., Muñoz-Bulnes, J., Portilla-Figueras, J. A., & Del Ser, J. (2015). One-year-ahead energy demand estimation from macroeconomic variables using computational intelligence algorithms. *Energy Conversion and Management*, *99*, 62–71.

Sánchez-Oro, J., Duarte, A., & Salcedo-Sanz, S. (2016). Robust total energy demand estimation with a hybrid Variable Neighborhood Search–Extreme Learning Machine algorithm. *Energy Conversion and Management*, *123*, 445–452.

Sarzaeim, P., Bozorg-Haddad, O., & Chu, X. (2018). Teaching-learning-based optimization (TLBO) algorithm. *Advanced Optimization by Nature-Inspired Algorithms*, 51–58.

Shehadeh, H. A. (2023). Chernobyl disaster optimizer (CDO): A novel meta-heuristic method for global optimization. *Neural Computing and Applications*, *35*(15), 10733–10749.

Sonmez, M., Akgüngör, A. P., & Bektaş, S. (2017). Estimating transportation energy demand in Turkey using the artificial bee colony algorithm. *Energy*, *122*, 301–310.

Sözen, A., Arcaklioğlu, E., & Özkaymak, M. (2005). Turkey's net energy consumption. *Applied Energy*, *81*(2), 209–221.

Tanyildizi, E., & Demir, G. (2017). Golden sine algorithm: a novel math-inspired algorithm. *Advances in Electrical & Computer Engineering*, *17*(2).

Tiris, M. (2005). Global trends for energy. *Turkish Workshop on Sustainable Development: Meeting the Challenges, JuØlich*.

Uguz, H., Hakli, H., & Baykan, Ö. K. (2015). A new algorithm based on artificial bee colony algorithm for energy demand forecasting in Turkey. *2015 4th International Conference on Advanced Computer Science Applications and Technologies (ACSAT)*, 56–61. IEEE.

Wilson, A. J., Pallavi, D. R., Ramachandran, M., Chinnasamy, S., & Sowmiya, S. (2022). A review on memetic algorithms and its developments. *Electrical and Automation Engineering*, *1*(1), 7–12.

Xue, J., & Shen, B. (2023). Dung beetle optimizer: A new meta-heuristic algorithm for global optimization. *The Journal of Supercomputing*, *79*(7), 7305–7336.

Yang, X.-S., & He, X. (2013). Bat algorithm: literature review and applications. *International Journal of Bio-Inspired Computation*, *5*(3), 141–149.

Yang, X.-S., & Slowik, A. (2020). Firefly algorithm. In *Swarm intelligence algorithms* (pp. 163–174). CRC Press.

Yumurtaci, Z., & Asmaz, E. (2004). Electric energy demand of Turkey for the year 2050. *Energy Sources*, *26*(12), 1157–1164.