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A Slime Mold Algorithm-Based Approach for Load Flow Analysis and Optimization in Power Systems

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Graphical/Tabular Abstract (Grafik Özet)

In this study, Slime Mold Algorithm was applied to OPF problems on IEEE-30 bus system to minimize fuel cost, power loss, and voltage deviation. / Bu çalışmada, yakıt maliyeti, güç kaybı ve gerilim sapmasını en aza indirmek amacıyla IEEE-30 baralı sistem üzerinde OGA problemlerine Balçık Küfü Algoritması uygulanmıştır.

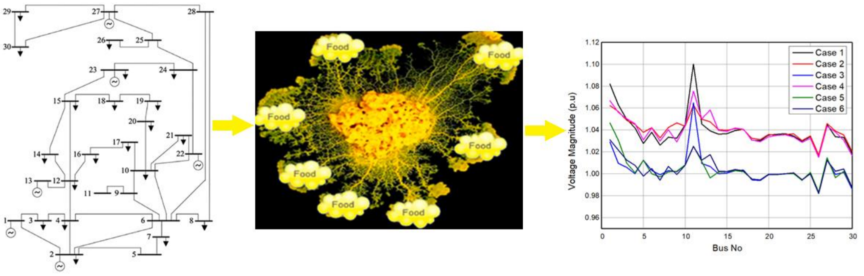

***Figure A**: Single line diagram of IEEE 30 bus power system, SMA algorithm figure and analysis result graphs. /**Şekil A:**.IEEE 30 baralı güç sisteminin tek hat şeması, BKA algoritma şekli ve analiz sonucu grafikleri.*

Highlights (Önemli noktalar)

- *SMA was successfully applied to OPF on IEEE-30 bus system. / BKA, IEEE-30 baralı sistemde OGA problemine başarıyla uygulanmıştır.*
- *Minimum voltage deviation (0.1013 p.u.) achieved with SMA. / En düşük gerilim sapması (0.1013 p.u.) BKA ile elde edilmiştir.*
- *SMA outperformed many algorithms in terms of power loss and cost. / BKA, güç kaybı ve maliyet açısından birçok algoritmadan daha başarılı sonuç vermiştir.*
- *SMA showed low sensitivity to parameter tuning. / BKA, parametre ayarlarına karşı düşük hassasiyet göstermiştir.*
- *High convergence speed and solution accuracy were observed. / Yüksek yakınsama hızı ve çözüm doğruluğu gözlemlenmiştir.*

***Aim (Amaç):** To solve OPF problems in power systems using Slime Mold Algorithm with single and multi-objective functions. / Güç sistemlerinde tekli ve çoklu amaç fonksiyonları ile Balçık Küfü Algoritması kullanılarak OGA problemlerini çözmek.*

***Originality (Özgünlük):** The study presents a comprehensive OPF analysis using SMA, evaluating six distinct objective function scenarios for the first time. / Bu çalışma, altı farklı amaç fonksiyonu senaryosu değerlendirerek BKA ile kapsamlı bir OGA analizi sunmaktadır.*

***Results (Bulgular):** SMA achieved minimum fuel cost of $800.66/h, power loss of 3.11 MW, and voltage deviation of 0.1013 p.u., outperforming benchmark algorithms. / BKA, $800.66/saat yakıt maliyeti, 3.11 MW güç kaybı ve 0.1013 p.u. gerilim sapması ile literatürdeki algoritmalardan daha iyi sonuçlar elde etmiştir.*

***Conclusion (Sonuç):** SMA is a robust and efficient algorithm for OPF problems, offering high performance and consistency across different scenarios. / BKA, farklı senaryolarda yüksek performans ve tutarlılık sağlayarak OGA problemleri için sağlam ve verimli bir algoritma olduğunu göstermiştir.*

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A Slime Mold Algorithm-Based Approach for Load Flow Analysis and Optimization in Power Systems

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Abstract

Electric energy is one of the most commonly used energy sources today. Therefore, how energy can be produced, transmitted, and consumed at the lowest cost is among the main topics that researchers are intensely working on. The limited nature of current energy sources and the rapidly increasing demand for energy necessitate scientific and technological efforts in this field. As the global economy grows and modern power systems continue to expand, the voltage problems arising in power systems have become quite significant in terms of controlling energy systems. In this context, one of the most important issues that need to be addressed in power systems is optimal power flow (OPF). Therefore, in the study conducted, the Slime Mold Algorithm (SMA) was used to solve the Optimal Power Flow (OPF) problem in power systems based on various objective functions, and it was tested with different objective functions. As the objective function, three single objectives (fuel cost, active power loss, and voltage deviation minimization) and the combination of these objective functions, three multi-objective functions, have been determined. The tests conducted to solve the OPF problem were carried out on the IEEE-30 bus system. According to the results obtained, it has been observed that the SMA algorithm is more successful than other algorithms in the literature in solving problems in power systems.

Güç Sistemlerinde Yük Akış Analizi ve Optimizasyonu için Balçık Küfü Algoritması Yaklaşımı

Makale Bilgisi

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Öz

Elektrik enerjisi, günümüzde en yaygın biçimde kullanılan enerji kaynakların başında gelmektedir. Bu nedenle, enerjinin en uygun maliyetle nasıl üretileceği, iletileceği ve tüketileceği araştırmacılar tarafından üzerinde yoğun şekilde çalışılan başlıca konular arasında yer almaktadır. Mevcut enerji kaynaklarının sınırlı olması ve buna karşılık enerjiye olan talebin hızla artması, bu alandaki bilimsel ve teknolojik çalışmaların gerekliliğini zorunlu kılmaktadır. Büyüyen bir dünya ekonomisiyle modern güç sistemlerinin her geçen gün biraz daha gelişmesi ve büyümesiyle birlikte güç sistemlerinde oluşan gerilim problemleri nedeniyle, enerji sistemlerinin kontrol altına alınması bakımından oldukça önem arz etmektedir. Bu bağlamda, güç sistemlerinde optimal güç akışı (OGA) üzerinde çalışılması gereken en önemli konulardan biridir. Dolayısıyla yapılan çalışmada, güç sistemlerinde amaç fonksiyonlarına göre OGA probleminin çözümünde Balçık Küfü Algoritması (BKA) kullanılmış ve farklı amaç fonksiyonlarında test edilmiştir. Amaç fonksiyonu olarak üç adet tekli (yakıt maliyeti, aktif güç kaybı ve gerilim sapması minimizasyonu) ve bu amaç fonksiyonlarının kombinasyonu üç adet çoklu amaç fonksiyonu belirlenmiştir. OGA probleminin çözümü için yapılan testler IEEE-30 baralı sistem üzerinden gerçekleştirilmiştir. Elde edilen sonuçlara göre BKA algoritmasının güç sistemlerindeki problemleri çözmede literatürdeki diğer algoritmalardan daha başarılı olduğu gözlemlenmiştir.

1. INTRODUCTION (GİRİŞ)

Today, the increase in the world population, industrialization, and technological advancements, along with the rise in living standards, are causing the demand for electrical energy to continuously increase. In order to meet the increasing demands of end users, operating transmission lines at maximum capacity and restructuring energy systems have become increasingly important. Consequently, determining how to produce, transmit, and consume energy at minimal cost is a central focus of current

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research. Limited resources and the rapid increase in both production and consumption demands necessitate the development of comprehensive and sustainable solutions in the energy sector. Additionally, the variability in supply and demand, along with the impact of environmental factors, increases the need for new meta-heuristic methods and innovative technologies on a global scale [1].

For an optimized electrical power system to operate smoothly, it must consist of various components that are integrated and work in harmony with each other. For this system to operate at full capacity and efficiently, it is essential for all components to work effectively and in a coordinated manner [2]. For this, the electrical industry, particularly the transmission line technology, needs to continuously improve its production, distribution, storage, and maintenance processes. The continuous improvement of these processes plays a critical role in strengthening the existing infrastructure against extreme weather conditions and extraordinary natural disasters [3]. Additionally, innovative strategies should be developed to enhance the reliability of electrical grids, ensure the resilience of infrastructure, and strengthen resistance against potential outages. Therefore, conducting continuous improvement efforts for the safety and sustainability of electrical power systems is considered one of the fundamental requirements of the energy sector [4].

In addition, due to the long distance between the produced electricity and the consumption points, it necessitates the transportation of energy through long transmission lines. However, this situation brings various technical challenges and systemic problems in energy transmission. Especially for energy transmission over long distances, it is necessary to minimize the losses that occur along the transmission lines. However, long-distance transmission also brings up problems critical to system safety, such as voltage stability [5]. In this context, various meta-heuristic methods have been used individually or in combination in the literature to reduce transmission losses and solve the systemic problems caused by these losses.

Farhat et al. proposed a slime mold algorithm (ESMA) developed based on the neighborhood dimension learning (NDL) search strategy for solving the OPF problem. The effectiveness of ESMA was verified using 23 benchmark functions and evaluated by comparing it with the original SMA and three new optimization algorithms [6]. ElSayed and Elattar formulated the optimal reactive power dispatch (ORPD) problem combined with renewable energy sources into a single objective function with coefficients, derived from five different objective functions with various operational constraints. Later, they tested and demonstrated the SMA technique on the IEEE-30 bus system and the IEEE-118 bus system using different scenarios [7]. Ermiş and Taşdemir analyzed the optimal placement and sizing of Distributed Generation (DG) systems and compared the performance of the Artificial Bee Colony (ABC) and JAYA algorithms. In the evaluations conducted on the IEEE-33 bus distribution system, they argued that JAYA was superior in terms of faster convergence and power loss reduction, while ABC was more successful in improving voltage profiles [8]. Kareem et al. presented an optimized droop control strategy to address power fluctuations caused by the variability of renewable energy sources and the unpredictable behavior of loads. They optimized the PI controller parameters using the Sine Cosine Algorithm (SCA) and the Sparrow Search Algorithm (SSA) and aimed to increase frequency-voltage stability in microgrids [9]. Mehmet et al. argued that the Fast Decoupled method can be preferred instead of the Newton-Raphson method up to 30 busbar power systems for cases where faster load flow analysis is required [10].

In this study, the reduction of transmission losses and the resolution of systemic problems caused by these losses were achieved using SMA, one of the meta-heuristic methods. Undesirable situations occurring in transmission lines have been applied to the IEEE-30 bus system under different scenarios. SMA has minimized OPF problems with its ability to effectively navigate the solution space and produce solutions close to the global optimum, low parameter sensitivity, and high convergence speed.

2. ANALYTICAL DEFINITION AND FORMULATION OF LOAD FLOW PROBLEM (YÜK AKIŞI PROBLEMİNİN ANALİTİK TANIMI VE FORMÜLASYONU)

In order to perform load flow analysis properly, the following four variables associated with each bus *i* in the system must be known.

$P_i =$ Active Power

$Q_i =$ Reactive Power

$V_i =$ Voltage Amplitude

$\delta_i =$ Phase Angle

In solving a problem, it is usually sufficient to know two of these four variables. In load flow analysis, two known parameters are used to calculate the other two unknown variables so that the state of the system can be determined.

The bus current is shown in Eq. 1, depending on the bus voltage and power.

$$I_i = \frac{S_{Gi}}{V_i} = \frac{(S_{Gi} - S_{Li})}{V_i} = \frac{(P_{Gi} - P_{Li}) - j\,(Q_{Gi} - Q_{Li})}{V_i} \quad (1)$$

If the current, admittance, and voltage are expressed in terms of Eq. 1, Eq. 2 is obtained.

$$\frac{(P_{Gi} - P_{Li}) - j\,(Q_{Gi} - Q_{Li})}{V_i} = Y_{i1} V_1 + Y_{i2} V_2 +, \dots , + Y_{in}$$
$$i = 1,2,\dots,n \quad (2)$$

The active and reactive power equations in the *i* bar are shown as follows.

$$P_i = P_{Gi} - P_{Li} \quad (3)$$

$$Q_i = Q_{Gi} - Q_{Li} \quad (4)$$

Equations in Eq. 3 and Eq. 4 if the equation in Eq. 2 is substituted into the equation in Eq. 5 and Eq. 6 are obtained.

$$\frac{(P_i - jQ_i)}{(V_i)} = \sum_{j=1}^{n} Y_{ij} V_j , \qquad i = 1,2, \dots , n \quad (5)$$

$$P_i - jQ_i = V_i \sum_{j=1}^{n} Y_{ij} V_j \qquad i = 1,2, \dots , n \quad (6)$$

The apparent power in a power system with *i* bars is expressed by Eq. 7 and Eq. 8.

$$S_i = P_i + JQ_i = V_i I_i^* \qquad i = 1,2, \dots , n \quad (7)$$

$$S_i = P_i - JQ_i = V_i^* I_i \qquad i = 1,2, \dots , n \quad (8)$$

Here, V_i is the voltage of the *i*-th bar with respect to the ground, and I_i is the source current flowing through the *i*-th bar. If the equations in Eq. 3 and Eq. 4 are substituted into the equation in Eq. 2, the equations in Eq. 9 and Eq. 10 are obtained.

$$I_i = \sum_{k=1}^{n} Y_{ik} V_k \quad (9)$$

$$S_i = P_i - JQ_i = V_i^* \sum_{k=1}^{n} Y_{ik} V_k$$
$$i = 1,2, \dots , n \quad (10)$$

If the real and imaginary components of the equation are expressed separately;

$$P_i\ (Active\ Power) = Re\,\{V_i^* \textstyle\sum_{k=1}^{n} Y_{ik} V_k\} \quad (11)$$

$$Q_i (Reactive\ Power) = -Im\{V_i^* \textstyle\sum_{k=1}^{n} Y_{ik} V_k\} \quad (12)$$

In a power system with *n* busbars, the active and reactive power values of the load busbars are given in Eq. 13 and Eq. 14.

$$P_i (Active\ Power) = |V_i| \sum_{k=1}^{n} |V_k||Y_{ik}| \cos(\theta_{ik} + \delta_k - \delta_i)$$
$$i = 1,2, \dots , n \quad (13)$$

$$Q_i (Reactive\ Power) = -|V_i| \sum_{k=1}^{n} |V_k||Y_{ik}| \sin(\theta_{ik} + \delta_k - \delta_i)$$
$$i = 1,2, \dots , n \quad (14)$$

When all power components are determined through Eq. 13 and Eq. 14, the power losses in the system are also simultaneously detected.

Active and reactive power losses are expressed in the formulas in Eq. 15 and Eq. 16.

$$P_L = \textstyle\sum_i P_{Gi} - \sum_i P_{Li} \quad (15)$$

$$Q_L = \textstyle\sum_i Q_{Gi} - \sum_i Q_{Li} \quad (16)$$

Here, P_{Gi} and Q_{Gi} are the active and reactive generator powers, and P_{Li} and Q_{Li} are the active and reactive load powers.

2.1. Objective Function (Amaç Fonksiyonu)

In power systems, three main objective functions have been identified for the OPF problem. Of these objective functions, 3 are single-objective functions and 3 are multi-objective functions, making a total of 6 cases in which optimization studies have been conducted.

2.1.1. Minimization of basic fuel cost (Temel yakıt maliyetinin minimize edilmesi)

In power systems, the objective function has been determined to minimize fuel costs by adjusting the production values of the generators. The fuel cost objective function is given in Eq. 17.

$$F_{cost} = \sum_{i=1}^{NG} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \quad (17)$$

Here, F_{cost} represents the fuel cost objective function, *NG* is the number of generators, and the given a_i, b_i, and c_i values show the cost coefficients for each generator. The generator coefficients are shown in Table 1.

Table 1. Generator cost coefficients (Jeneratör maliyet katsayıları)

	Cost Coefficients		
Bus No.	*a*	*b*	*c*
1	0.00	2.00	0.00375
2	0.00	1.75	0.01750
5	0.00	1.00	0.06250
8	0.00	3.25	0.00834
11	0.00	3.00	0.02500
13	0.00	3.00	0.02500

2.1.2. Minimization of power loss (Güç kaybının minimize edilmesi)

The objective function aimed at minimizing active power losses occurring in transmission lines in power systems is shown in Eq. 18.

$$P_{loss} = \sum_{i=1}^{nl} \sum_{j\neq 1}^{nl} G_{ij}\left[V_i^2 + V_j^2 - 2V_iV_j cos(\delta_i - \delta_j)\right] \tag{18}$$

Here, P_{loss} denotes the power loss objective function, *nl* the number of transmission lines, and G_{ij} the conductivity value between the lines.

2.1.3. Minimization of voltage deviation (Gerilim sapmasının minimize edilmesi)

Eq. 19 was used to calculate the bus voltage deviation value on the system.

$$V_D = \sum_{l=1}^{N_L} |V_L - 1| \tag{19}$$

Here, V_D voltage deviation is the objective function, N_L is the number of load buses, and V_L is the load bus voltage.

3. SLIME MOULD ALGORITHM (BALÇIK KÜFÜ ALGORİTMASI)

The Slime Mold Algorithm (SMA) is a dynamic optimization algorithm based on the oscillatory behavior exhibited by the unicellular organism Physarum polycephalum in its natural environment, mimicking only the feeding process instead of the entire life cycle. Introduced to the literature in 2020 by Li and colleagues, the SMA is a community-based meta-heuristic optimization algorithm that is based on the access of slime mold patterns, which respond to airborne odors, to food sources [11]. The algorithm is simulated by modeling it in three basic stages: approaching food, wrapping food, and oscillation [12]. Figure 1 shows the nutritional morphology of the slime mold.

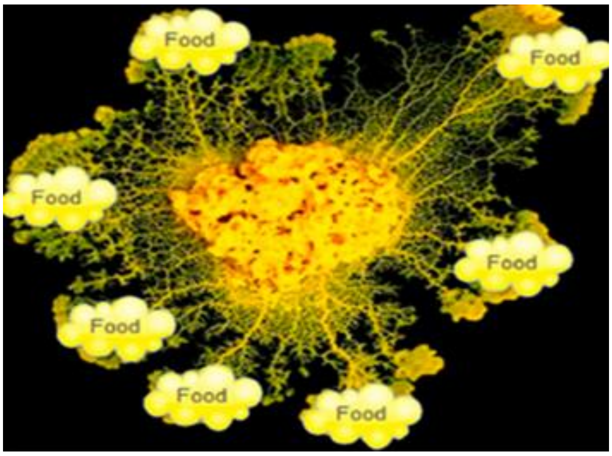

Figure 1. The feeding morphology of the mud fungus (Balçık küfü beslenme morfolojisi) [13]

3.1. Approach to Food (Yiyeceklere Yaklaşım)

In the food approach phase, the slime mold organism is directed towards the food source based on the level of odor concentration in the air. This approach behavior has been mathematically expressed in Eq. 20 [14].

$$\overrightarrow{X_{(t+1)}} = \begin{cases} \overrightarrow{X_b(t)} + \overrightarrow{vb}.\left(\overrightarrow{W}.\overrightarrow{X_A(t)} - \overrightarrow{X_B(t)}\right) & r < p \\ \overrightarrow{vc}.\overrightarrow{X(t)} & r \geq p \end{cases} \tag{20}$$

Here, $\overrightarrow{vb}$ [-a, a] is a parameter that falls within the range of negative value (-1) to positive value (+1), and $\overrightarrow{vc}$ is a number that linearly decreases from 1 to 0. $\overrightarrow{X(t)}$ indicates the current location of the slime mold. $\overrightarrow{X_b(t)}$ is the individual position corresponding to the highest odor concentration found so far, and *(t)* indicates the number of iterations up to that point. $\overrightarrow{X_A(t)}$ and $\overrightarrow{X_B(t)}$ are two different individuals randomly selected from the slime mold, respectively. $\overrightarrow{W}$ represents the weight of the clay fungus. *r* (rand) represents a randomly generated random number between 0 and 1. *p* and *a* are calculated using the formulas in Eq. 21 and Eq. 22, respectively.

$$p = \tan h|S(i) - DF|, \quad i \in 1,2,\dots,N \tag{21}$$

$$a = \arctan h\left(-\left(\frac{t}{\max\_t}\right) + 1\right) \tag{22}$$

Here, $i \in 1,2,...,N$ represents the fitness function value *S(i)* of the vector $\vec{X}$. *DF* is the best optimal fitness value obtained in all iterations. *max_t* is the maximum number of iterations set for the algorithm. The mathematical representation of the weight vector $\overrightarrow{W}$ associated with the clay lump is formulated in Eq. 23 below.

$$\overrightarrow{W(smell\_index(i))} = \left\{1 + r.\log\left(\frac{bF - S(i)}{bF - wF} + 1\right), cond.\right.$$

$$\overrightarrow{W(smell\_index(i))} = \left\{1 - r.\log\left(\frac{bF - S(i)}{bF - wF} + 1\right), oth.\right.$$

$$\text{smell\_index} = \text{sort}\,(S) \tag{23}$$

Here, *r* represents a randomly generated number in the range [0,1]. The maximum number of iterations is denoted by *maks_t*, the best fitness value in the current iteration is denoted by *bF*, and the worst fitness value is denoted by *wF*. *smell_index* is defined as an evaluation criterion based on the principle of sorting the fitness function values in the search space from minimum to maximum or from maximum to minimum.

3.2. Wrapping Food (Yiyecekleri Sarma)

This approach allows for the mathematical simulation of the contraction mechanism of the slime mold in the venous tissue structure. When the vascular structure contracts towards a nutrient source at a high concentration, the slime mold generates a strong wave, leading to a rapid cytoplasmic flow and an increase in vessel thickness. This relationship between food concentration and vessel width is mathematically simulated by Eq. 23. In this context, the weight of the slime mold increases in areas with high nutrient concentration, while in areas with low nutrient concentration, the weight decreases, allowing for the exploration of alternative regions. The position update process of the slime mold individuals is carried out through the mathematical formula expressed by Eq. 24 [15].

$$\overrightarrow{X^*} = \begin{cases} rand.(UB - LB) + LB, & rand < z \\ \overrightarrow{X_b(t)} + \overrightarrow{vb}.\left(W.\overrightarrow{X_A(t)} - \overrightarrow{X_B(t)}\right), & r < p \\ \overrightarrow{vc}.\overrightarrow{X(t)}, & r \geq p \end{cases} \tag{24}$$

Here, UB and LB represent the upper and lower bounds of the food search range. r and rand represent the randomly generated values in the range [0, 1]. z, on the other hand, is a parameter that optimizes the balance between research and usage.

3.3. Oscillation (Osilasyon)

The oscillation phase of the slime mold is controlled by a biological oscillator. This oscillator generates a wave of propagation that alters the cytoplasmic flow in the vessels. This process determines the tendency of the vessels to be in a more favorable position in terms of nutrient concentration. In this context, $\overrightarrow{W}$, $\overrightarrow{vb}$, and $\overrightarrow{vc}$ are used to simulate the changes in the venous width of the mud fungus [16]. The slime mold moves faster in areas with higher food concentrations, while its movement speed decreases in areas with lower concentrations. This behavior allows the slime mold to select the optimal food source, thereby increasing its efficiency. The selective behavior of slime mold, represented by the synergistic interaction between $\overrightarrow{vb}$ and $\overrightarrow{vc}$, expresses the selective behavior of the slime mold [17]. This behavior continues to explore a higher quality food source even if a better food source has been found. It also prevents the slime mold from focusing on just one source. However, the decision to approach a food source or find new resources is simulated by the oscillation process of $\overrightarrow{vb}$. However, environmental constraints such as dry environments or light can hinder the movement of slime molds. This situation also does not allow for slime mold calculations.

4. SIMULATION RESULTS (SİMÜLASYON BULGULARI)

In this study, an optimization work was carried out to solve the OPF problem in the IEEE-30 bus power system using the SMA algorithm. To solve the OPF problem, objective functions were determined in 6 different scenarios, and the objective functions are provided in Table 2.

Table 2. Working conditions in test systems (Test sistemlerinde çalışma koşulları)

Name	Objective functions
Case 1	Minimization of basic fuel cost
Case 2	Minimization of power loss
Case 3	Minimization of voltage deviation
Case 4	Minimization of fuel cost and active power losses
Case 5	Minimization of fuel cost and voltage deviation
Case 6	Minimization of cost, losses, and voltage deviation

4.1. IEEE-30 Bus System (IEEE-30 Bus Sistemi)

The OPF solution has been tested on the IEEE-30 bus power system. This power system consists of 6 generators, 41 transmission lines, 4 transformers, and 9 shunt reactive power compensators. The load demanded from the power system is 283.4 MW of active power and 126.2 MVAr of reactive power. The voltage values of the buses in the system are limited to the range of 0.95-1.05 p.u. [18, 19]. The single-line diagram of the power system is shown in Figure 2. The analysis results of the objective functions considered in the OPF problem solution are also presented in Table 3.

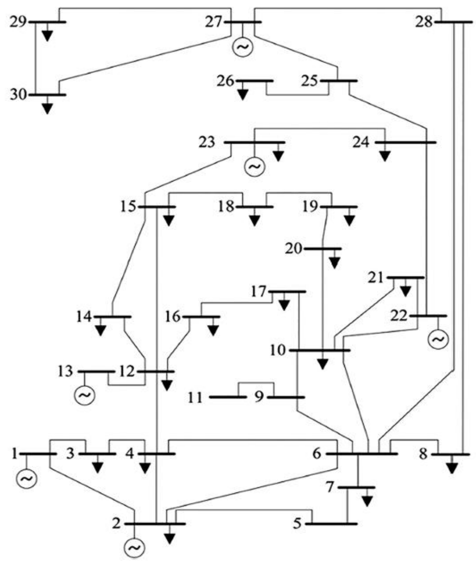

Figure 2. Single-line diagram of the IEEE-30 bus power system (IEEE-30 baralı güç sisteminin tek hat şeması)

Table 3. OPF test results for SMA algorithms in cases for IEEE-30 bus (IEEE-30 bara için SMA algoritmalarının OPF test sonuçları)

	Limits Min	Limits Max	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
P_{g1}(MW)	50	250	177.4209	51.5129	206.7478	102.3816	173.9549	97.3952
P_{g2}(MW)	20	80	48.5288	80.0000	20.0000	55.7455	48.3398	58.7123
P_{g5}(MW)	15	50	21.7860	50.0000	16.3524	38.0808	21.5816	37.9406
P_{g8}(MW)	10	35	20.7981	35.0000	10.0000	35.0000	23.9423	35.0000
P_{g11}(MW)	10	30	11.9409	30.0000	30.0000	30.0000	13.1647	29.8817
P_{g13}(MW)	12	40	12.0000	40.0000	12.0000	26.7440	12.0000	29.2402
V_{g1}(p.u)	0.95	1.1	1.0819	1.0622	1.0290	1.0666	1.0463	1.0309
V_{g2}(p.u)	0.95	1.1	1.0629	1.0569	1.0095	1.0560	1.0307	1.0215
V_{g5}(p.u)	0.95	1.1	1.0275	1.0378	1.0123	1.0308	1.0123	0.9978
V_{g8}(p.u)	0.95	1.1	1.0333	1.0422	1.0028	1.0401	1.0016	1.0067
V_{g11}(p.u)	0.95	1.1	1.1000	1.0626	1.0647	1.0754	1.0251	1.0248
V_{g13}(p.u)	0.95	1.1	1.0391	1.0474	1.0066	1.0582	0.9962	1.0174
T_{6-9}(p.u)	0.9	1.1	1.1000	1.0032	1.0778	1.0880	1.0302	1.0460
T_{6-10}(p.u)	0.9	1.1	0.9000	0.9814	0.9359	0.9000	0.9000	0.9073
T_{4-12}(p.u)	0.9	1.1	0.9811	0.9869	0.9662	0.9981	0.9443	0.9838
T_{28-27}(p.u)	0.9	1.1	0.9751	0.9762	0.9691	0.9768	0.9631	0.9757
Q_{C10}(MVAr)	0	0.05	4.3057	5.0000	5.0000	4.2801	1.2011	2.3568
Q_{C12}(MVAr)	0	0.05	5.0000	5.0000	0.0000	5.0000	0.1087	0.0000
Q_{C15}(MVAr)	0	0.05	5.0000	5.0000	4.5877	4.7340	4.7897	3.6314
Q_{C17}(MVAr)	0	0.05	5.0000	5.0000	4.2133	5.0000	1.5163	2.8337
Q_{C20}(MVAr)	0	0.05	4.6435	5.0000	5.0000	3.4964	5.0000	5.0000
Q_{C21}(MVAr)	0	0.05	5.0000	5.0000	5.0000	5.0000	4.7050	5.0000
Q_{C23}(MVAr)	0	0.05	3.9034	4.0546	5.0000	2.4573	4.6131	5.0000
Q_{C24}(MVAr)	0	0.05	5.0000	5.0000	5.0000	5.0000	4.2470	5.0000
Q_{C29}(MVAr)	0	0.05	2.6716	3.0822	2.9396	2.3298	2.5522	4.1234
Obj. Func.			800.6629	3.1129	0.1013	1041.4089	814.7635	1070.1887
F_{cost}(\$/h)			800.6629	967.6931	834.2872	859.3021	803.5856	866.3723
P_{loss}(MW)			9.0748	3.1129	11.7003	4.5519	9.5833	4.7700
V_D(pu)			0.8433	0.8977	0.1013	0.8523	0.1118	0.1302

4.1.1. Case 1: Minimization of basic fuel cost (Vaka 1: Temel yakıt maliyetinin minimize edilmesi)

In Case 1, the goal is to minimize the total fuel cost of energy production in the power system. The minimization of fuel cost is calculated according to Eq. 17. The coefficients *a*, *b*, and *c* given in the equation are provided in Table 1 [19]. In Case 1, the fuel cost values are provided in Table 4. According to the SMA algorithm, the fuel cost was calculated as 800.6629 \$/hr. The convergence graph of the objective function is provided in Figure 3(a). The comparison with studies in the literature aimed at minimizing fuel costs is presented in Table 4, and it has been determined that more minimal results were achieved compared to other methods.

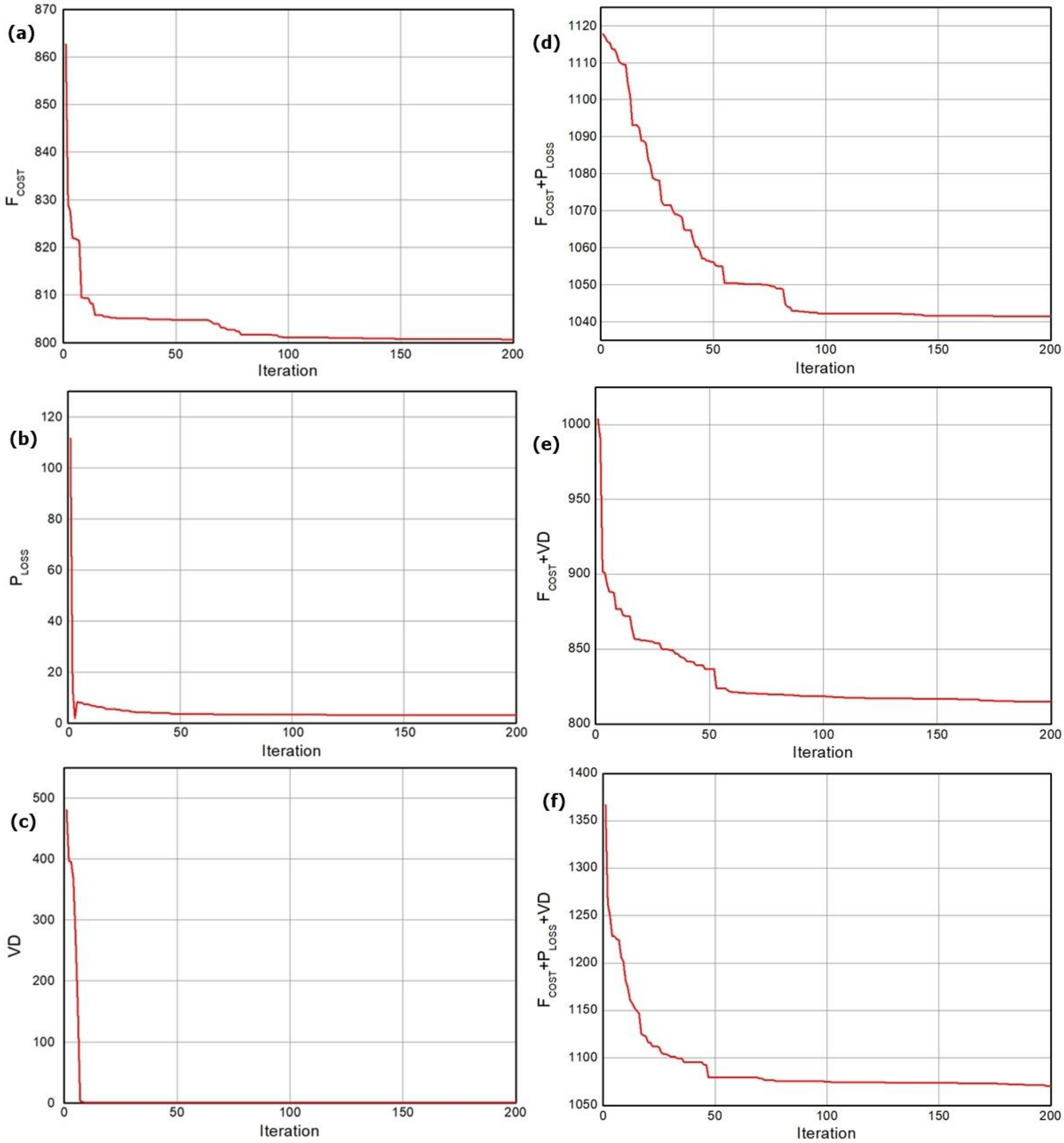

Figure 3. Iteration graph of objective functions in all cases (a) Case 1, (b) Case 2, (c) Case 3, (d) Case 4, (e) Case 5, (f) Case 6 (Tüm durumlardaki amaç fonksiyonlarının yineleme grafiği (a) Durum 1, (b) Durum 2, (c) Durum 3, (d) Durum 4, (e) Durum 5, (f) Durum 6)

Table 4. Comparison of OPF solutions for Case 1 (Durum 1 için OPF çözümlerinin karşılaştırılması)

Algorithm	F_{cost} (\$/hr]	P_{loss} (MW)	V_D (pu.)
SMA	***800.6629***	9.0948	0.8433
TLBO [20]	801	9.1875	0.8269
MSO [21]	801.571	9.2767	
CEO [22]	800.9771	9.0598	1.17
GA [23]	800.7666	8.9882	0.8228
GWO [24]	800.9308	9.0558	0.724

4.1.2. Case 2: Minimization of power loss (Vaka 2: Güç kaybının minimize edilmesi)

Minimizing power loss in power systems has been examined in Case 2. The objective function for minimizing power loss is specified in Eq. 18. In Table 5, the Ploss value for Case 2 has been calculated as 3.1129 MW, and the convergence graph is shown in Figure 3(b). In the literature comparisons, it is observed in Table 5 that the SMA algorithm yielded better results in terms of power loss.

Table 5. Comparison of OPF solutions for Case 2
(Durum 2 için OPF çözümlerinin karşılaştırılması)

Algorithm	F_{cost} ($/hr]	P_{loss} (MW)	V_D (pu.)
SMA	967.6931	***3.1129***	0.8977
TLBO [20]	965.9766	3.1794	0.7133
MSO [21]	968.314	3.4052	
EGA [25]	967.86	3.2008	0.12178
GA [23]	967.5342	3.1342	0.8739
FPA [26]	967.1138	3.5661	0.3893

4.1.3. Case 3: Minimization of voltage deviation (Vaka 3: Gerilim sapmasının minimize edilmesi)

In Case 3, the system was optimized to minimize the voltage deviation value at the busbars. In Case 3, the optimization results are given as 0.1013 p.u in Table 6. According to all cases, the case with the lowest voltage deviation value is obtained in SMA optimization. In addition, when the SMA algorithm is compared with other studies in the literature, it is seen in Table 6 that it gives better results than other algorithms and the convergence graph is shown in Figure 3(c).

Table 6. Comparison of OPF solutions for Case 3
(Durum 3 için OPF çözümlerinin karşılaştırılması)

Algorithm	F_{cost} ($/hr]	P_{loss} (MW)	V_D (pu.)
SMA	934.2872	11.7003	***0.1013***
TLBO [20]	814.47	8.3236	0.1077
EGA [25]	898.817	6.092	0.10402
AGA [27]	805.8096	10.6097	0.1207
BHBO [28]	804.5975	9.5778	0.1262
DE [29]	805.2619		0.1357

4.1.4. Case 4: Minimization of fuel cost and active power losses (Vaka 4: Yakıt maliyetinin ve aktif güç kayıplarının minimize edilmesi)

Multiple objective functions are targeted here. Two objective functions, fuel cost and active power loss minimization, are optimized simultaneously. The results of the analysis are shown in Table 7. According to the results, F_{cost} is calculated as 859.3021 $/hr and P_{loss} is calculated as 4.5519 MW. The superiority of SMA in the literature is shown in Table 7. As can be seen from Figure 3(d), the convergence graph is higher than the other cases.

Table 7. Comparison of OPF solutions for Case 4
(Durum 4 için OPF çözümlerinin karşılaştırılması)

Algorithm	F_{cost} ($/hr]	P_{loss} (MW)	V_D (pu.)
SMA	***859.3021***	***4.5519***	0.8523
GA [23]	859.5349	4.5651	0.8689
PSO [23]	858.6638	4.5724	0.9225
GOA [23]	861.8316	4.6645	0.7143
MFO [26]	858.5812	4.5772	0.89944

4.1.5. Case 5: Minimization of fuel cost and voltage deviation (Durum 5: Yakıt maliyetinin ve gerilim sapmasının minimize edilmesi)

The fuel cost and voltage deviation multiple objective function is analyzed in Case 5. The objective is to optimize the fuel cost and voltage deviation simultaneously. According to the analysis results, F_{cost} and V_D values are calculated as 803.5856 $/hr and 0.1118 p.u respectively. The analysis results are shown in Table 8 and Figure 3(e) shows the convergence graph.

Table 8. Comparison of OPF solutions for Case 5
(Durum 5 için OPF çözümlerinin karşılaştırılması)

Algorithm	F_{cost} ($/hr]	P_{loss} (MW)	V_D (pu.)
SMA	***803.5856***	9.5833	***0.1118***
TLBO [20]	804.72	9.6786	0.1218
DE [29]	805.2619	10.4412	0.1357
BBO [30]	804.9982	9.95	0.102
CEO [22]	804.6734	10.0675	0.1102

4.1.6. Case 6: Minimization of cost, losses, and voltage deviation (Maliyet, kayıp ve gerilim sapmasının minimize edilmesi)

In Case 6, it is aimed to minimize all three objective functions F_{cost}, P_{loss} and V_D at the same time. In this case, F_{cost}, P_{loss} and V_D values are calculated as 866.3723 $/hr, 4.7700 MW, 0.1302 p.u respectively in Table 3 and Figure 3(f) shows the convergence graph after 200 iterations.

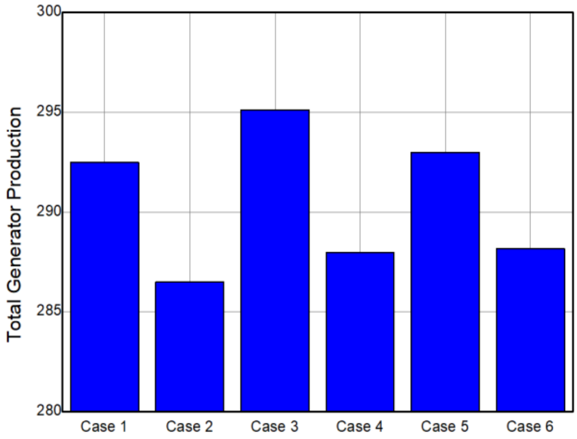

Figure 4. Total generator generation graph in all cases (Tüm durumlardaki toplam jeneratör üretim grafiği)

As can be seen from the total production graph of the generators in Figure 4, Case 2 is the situation where the least generator production occurs. In this case, the minimization of active power loss has been targeted. Active power loss is calculated as the difference between total production and total demand. Here, the total generator output is at its lowest value, resulting in an active power loss of 3.1129 MW at a minimum level. In Case 3, the total generator production value is the highest. In this case, voltage deviation minimization has been determined as the objective function. To bring the bus voltage value closer to 1 p.u., the total generator output value in the system was maximized, and the voltage deviation value was calculated to be 0.1013 p.u., which is the lowest value in all cases.

Table 9. Analysis statistics for all cases (Tüm durumların analiz istatistikleri)

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Best	800.6629	3.1129	0.1013	1041.4089	814.7635	1070.1887
Worst	801.5287	3.3012	0.1447	1046.7840	819.2429	1076.2965
Mediocre	800.9536	3.1670	0.1226	1043.7320	817.0436	1072.0488
Standard Deviation	0.2043	0.0004	0.0100	1.3223	1.0989	1.2487
Time (sn)	16.1745	18.5045	15.6671	28.0541	24.4877	32.4215

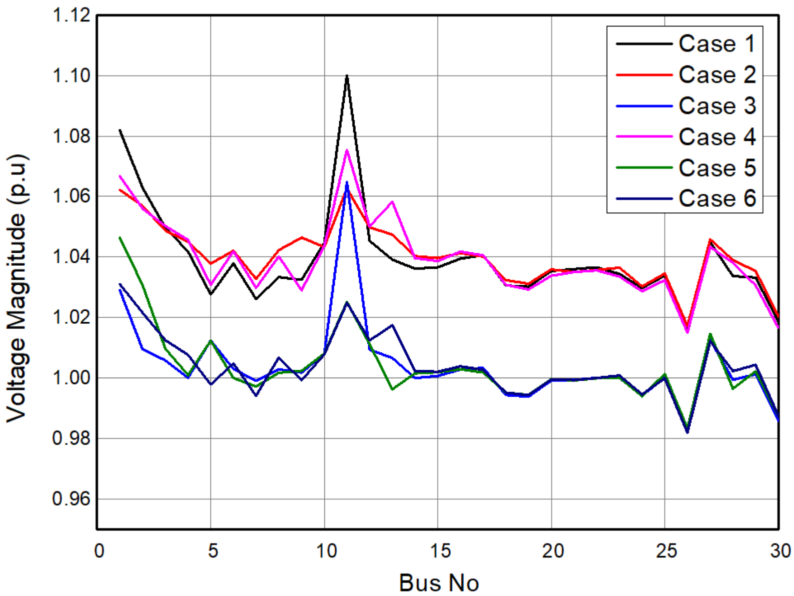

Figure 5. Bar voltage graph in all cases (Tüm durumlardaki bara gerilim grafiği)

Table 9 shows the statistical results obtained with the SMA algorithm. In the conducted study, it was observed that the standard deviation of the algorithm in single-objective functions yielded very low values. In this case, it has been observed that the algorithm is more consistent with single-objective functions compared to multi-objective functions. However, when comparing the algorithm's execution times, it has generally taken longer in scenarios with higher results or more fluctuations. This situation may indicate that the algorithm is trying to solve more complex or challenging problems.

Figure 5 shows the bus voltage values. As can be seen from Figure 5, in the single-purpose and multi-purpose scenarios where voltage deviation is targeted (Case 3, Case 5, Case 6), the bus voltage values are closest to 1 p.u. In other cases, the bus voltage has taken values above 1 p.u. However, the aim of the voltage deviation is to bring the bus voltage values closer to 1 p.u.

CONCLUSIONS (SONUÇLAR)

In this study, one of the nature-inspired heuristic methods, SMA, was applied to solve load flow analyses encountered in electrical power systems, and the effectiveness of this algorithm in OPF problems was examined in detail. The SMA algorithm was evaluated under six different scenarios on the IEEE-30 bus test system; analyses were conducted based on fundamental performance criteria such as fuel cost, active power loss, and voltage deviation, using both single and multi-objective functions. The results obtained show that the SMA algorithm can produce solutions with high accuracy in load flow analysis and provides lower fuel costs, minimum power loss, and more stable voltage profiles compared to classical methods. Especially, the lowest voltage deviation (0.1013 p.u.) obtained in the Case 3 scenario is a very positive result in terms of system stability. Similarly, the lowest active power loss of 3.1129 MW obtained in Case 2 is considered a significant achievement in enhancing system efficiency. The SMA algorithm has the potential to produce solutions close to the global optimum due to the adaptive relationship it establishes between exploration and exploitation in the search space. Additionally, its low sensitivity to parametric adjustments allows the algorithm to be easily applied to different power system models. In this respect, SMA stands out as a strong alternative optimization tool for both academic research and practical applications. In future studies, it is suggested to combine SMA with hybrid artificial intelligence techniques, apply it to larger-scale and dynamic systems, and test the algorithm's performance under different scenarios. Thus, it will be possible to enhance contributions towards operating energy systems in a safer, more efficient, and sustainable manner.

DECLARATION OF ETHICAL STANDARDS (ETİK STANDARTLARIN BEYANI)

The author of this article declares that the materials and methods they use in their work do not require ethical committee approval and/or legal-specific permission.

Bu makalenin yazarı çalışmalarında kullandıkları materyal ve yöntemlerin etik kurul izni ve/veya yasal-özel bir izin gerektirmediğini beyan ederler.

AUTHORS' CONTRIBUTIONS (YAZARLARIN KATKILARI)

***Oğuz TAŞDEMİR*:** He analyzed the results and carried out the article writing process.

Sonuçları analiz etmiş ve makale yazım işlemini gerçekleştirmiştir.

***Salih ERMİŞ*:** He analyzed the results and carried out the article writing process.

Sonuçları analiz etmiş ve makale yazım işlemini gerçekleştirmiştir.

***Abdülkadir ÖZDOĞAN*:** He conducted the literature review and determined the optimization technique.

Literatür taramasını gerçekleştirmiş ve optimizasyon tekniğini belirlemiştir.

CONFLICT OF INTEREST (ÇIKAR ÇATIŞMASI)

There is no conflict of interest in this study.

Bu çalışmada herhangi bir çıkar çatışması yoktur.

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