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RESEARCH ARTICLE

Cost Optimization for Sustainable Economy with Heuristic Algorithms in Power System

Güç Sisteminde Sezgisel Algoritmalarla Sürdürülebilir Ekonomi Amaçlı Maliyet Optimizasyonu

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ABSTRACT: Economically transmitting the energy obtained from power generation units through transmission and distribution lines is critical for environmentally friendly and sustainable energy management. The component that plays an important role in delivering electrical energy from production units to distribution and consumption units is the transmission/distribution network. At this stage, economic sustainability of the generated active and reactive power is possible by keeping operating costs and loss expenses under control. Insufficient power generation units or increased losses increase the operating costs in power systems. Capacity excess and cost increase affect stability by reducing system reliability. These negativities can cause problems in power systems and negatively affect consumers by making the power transmission network unusable. Developing technology and increasing energy demands bring quality problems in power systems. The operating costs of existing power generation units, which will provide the increasing demand power with the most appropriate cost and power generation, need to be revised with optimization techniques. Thus, the efficiency of power systems can be increased. If power systems are inadequate, new and renewable power generation units should be included in the power system. In this study, power system operation and cost optimizations were carried out with Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) algorithms that use swarm intelligence on IEEE 30-bus test systems. Significant differences in the results were observed when the number of population and re-runs were selected as 20, 30 and 50 for the PSO and GWO algorithms, respectively. When the results for three different situations are compared on the basis of algorithms; In the simulation tests conducted for the third case, where 50 population and re-run values of the PSO algorithm were used, the optimal operating cost value of 800.47 $/h was reached. As a result of the study, it was seen that the PSO and GWO algorithms used in the power system brought the total operating cost closer to minimum values and made power production more sustainable by increasing the number of population and re-runs.

Keywords: Power systems, sustainable energy, cost optimization, PSO, GWO.

ÖZ: Güç üretim birimlerinden elde edilen enerjinin iletim ve dağıtım hatları üzerinden ekonomik bir şekilde iletilmesi, çevre dostu ve sürdürülebilir enerji yönetimi açısından kritiktir. Elektrik enerjisinin üretim birimlerinden dağıtım ve tüketim birimlerine ulaştırılmasında önemli bir rol oynayan bileşen, iletim/dağıtım şebekesidir. Bu aşamada, üretilen aktif ve reaktif gücün ekonomik bir şekilde sürdürülebilirliği, işletme maliyetleri ve kayıp giderlerinin kontrol altında tutulması ile mümkündür. Güç üretim birimlerinin yetersiz olması veya kayıpların artması, güç sistemlerinde işletme maliyetini artırır. Kapasite aşımı ve maliyet artışı ise sistem güvenilirliğini azaltarak kararlılığı etkiler. Bu olumsuzluklar, güç sistemlerinde sorunlara yol açabilir ve güç iletim şebekesini kullanılamaz hale getirerek tüketicileri olumsuz etkiler. Gelişen teknoloji ve artan enerji talepleri, güç sistemlerinde kalite sorunlarını beraberinde getirmektedir. Artan talep gücünü en uygun maliyet ve güç üretimiyle sağlayacak mevcut güç üretim ünitelerinin işletme maliyetlerinin optimizasyon teknikleri ile revize edilmesi gerekmektedir. Böylelikle güç sistemlerinin verimliliği artırılabilir. Güç sistemlerinin yetersiz kalması durumunda yeni ve yenilenebilir güç üretim üniteleri güç

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sistemine dahil edilmelidir. Bu çalışmada, IEEE 30-bara test sistemleri üzerinde sürü zekasını kullanan Parçacık Sürü Optimizasyonu (PSO) ve Gri Kurt Optimizasyonu (GKO) algoritmaları ile güç sistemi işletme ve maliyet optimizasyonları gerçekleştirilmiştir. PSO ve GKO algoritmaları için popülasyon ve tekrar çalıştırma sayısı sırasıyla 20, 30 ve 50 değerlerinde seçildiğinde sonuçlarda önemli farklılıklar gözlemlenmiştir. Üç farklı durum için oluşan sonuçların algoritmalar bazında karşılaştırılması yapıldığında; PSO algoritmasının 50 popülasyon ve yeniden çalıştırma değerlerinin kullanıldığı üçüncü durum için yapılan simülasyon testlerinde en uygun işletme maliyet değeri olan 800,47 $/Saat'e ulaşılmıştır. Çalışma sonucunda güç sisteminde kullanılan PSO ve GKO algoritmalarının popülasyon ve tekrar çalıştırma sayısının artışıyla toplam işletme maliyetini asgari değerlere yaklaştırdığı ve güç üretimini daha sürdürülebilir hale getirdiği görülmüştür.

Anahtar Kelimeler: Güç sistemleri, sürdürülebilir enerji, maliyet optimizasyonu, PSO, GKO.

1. INTRODUCTION

Meeting the challenges of sudden increases in power demand in power systems can lead to potential issues such as the outage of transmission lines or generation units. To overcome such problems, strategies like restructuring power systems, organizing distributed generation, and implementing automatic load management and switchgear strategies are employed [1]. These methods enhance the security and reliability of power systems, providing end consumers with a higher level of energy quality [2]. Among the expectations of end consumers is the delivery of high-quality electrical energy sustainably at optimal costs. To achieve optimum energy costs, enhancing power system reliability by optimal placement of distributed generation units and minimizing transmission line losses is essential [3]. This way, delivering energy to end consumers at the most favourable cost with the lowest power system loss becomes possible.

Economic energy distribution has become a critical element in today's energy generation, transmission, and distribution, given the rise in energy demand and fossil fuel costs [4]. Therefore, transitioning to energy-saving and economic power distribution models has become a necessity [5]. Renewable energy sources used in distributed generation, such as wind, solar, biomass, biogas, etc., can inject active and reactive power into the power system or act as loads when needed [6]. Power plants based on renewable energy sources, with proper placement and accurate power and cost optimization, reduce power system losses, lower total energy costs, and contribute to minimizing global warming. Managing the current power demand and optimizing renewable energy-based generation for minimum energy costs and a sustainable environment have become indispensable today [7]. Generation costs of generation units are numerically defined to obtain minimum generation costs under current load conditions [8]. The cost function is generally determined as a second-degree nonlinear function. However, this may be insufficient on its own. Therefore, fuel costs and load conditions are also considered in this function. Additionally, transmission line losses and connection point power distribution conditions may require a more comprehensive evaluation, affecting economic power distribution [9]. The combustion of fossil fuels results in significant problems in terms of both climate change and costs. If the optimization problem is defined to provide economic power distribution; in addition to load allocation in power generation units, reliability, continuity of energy supply to demand, appropriate costs, and reduction of fossil fuels will significantly reduce climate change and environmental factor expenditures [10]. While metaheuristic algorithms have been evaluated in terms of efficiency and robustness in economic load distribution (ELD) of power systems in literature studies, in [11] the exploration and exploitation capabilities of clustering cuckoo search optimization have been verified in ELD problems with different numbers of generators. In ELD optimization studies of power systems, comparative solutions of classical metaheuristic algorithms and their hybrid versions have been evaluated in terms of quality and efficiency to solve single or multi-objective functions [12]. Among these methods, in [13], a modified objective function in a power system with wind energy included in MATLAB software and a comparative analysis of the results obtained by applying ELD simulations with the PSO technique were made, emphasizing the speed of PSO in optimal solutions and its effect on cost reduction. In the study [14], referring to the popularity of PSO, it was evaluated that the performance of the PSO architectural structures used in the studies was quite good in applications. The usefulness and calculation speed of PSO on various scenario situations of power systems and different IEEE bus test systems have been verified [15]. It has been confirmed in CEC functions that the developed GWO, while PSO applications are continuing, produces very assertive results in its use in the optimization of engineering problems and can be applied efficiently in optimization problems [16]. GWO algorithm was subjected to performance tests in the solution of very limited optimization problems using IEEE bus test systems data in the analysis of power systems and successful results were obtained [17]. Although these metaheuristic algorithms tend to get stuck in local minima, they achieve near-optimal results in function solutions. In addition to the metaheuristic algorithms mentioned in the allocation process of ELD, Whale Optimization Algorithm (WOA) etc. [18] algorithms produce effective solutions without getting stuck in local optimum in order to minimize the operating costs of power systems and production units as much as possible. In economical load distribution, mathematical optimization methods can analyse cost functions related to production costs. When defining functions, inputs and outputs in production units need to be formulated. In this context, fuel and its entry points into the system can be defined as input. Environmental sensitivity and fuel-related emissions play an important role in defining the function for economical load distribution. Economical load distribution based on power generation, taking into account load demand, can significantly reduce fuel consumption and emission levels in the system [19].

In this study, cost optimizations of the power system were made using PSO and GWO smart-based algorithms on the IEEE 30-bus test system for economic power distribution. A single objective function was used to minimize fuel usage, emissions, and power losses to optimize power generation and transmission costs. Three cases with different population and re-run numbers were analysed in order to reveal the effects of the population number and number of runs on the use of algorithms and to evaluate the performance of the objective functions. The results obtained are presented by comparing the performances of the algorithms.

The sections of the study are organized as follows: Section 2, under the title ‘Materials and Methods’, begins with a definition of the problem and an introduction to the bus system used. Subsequently, detailed explanations of the PSO and GWO algorithms employed for optimization are provided, including flowcharts. Section 3 presents comparative results of the PSO and GWO optimizations conducted for three cases on the IEEE 30-bus test system, using various parameters. In Section 4, the outcomes of this study are juxtaposed with previous research findings on the same test system, emphasizing the positioning of this study within the existing literature. Conclusions and evaluations are presented in Section 5.

2. MATERIALS AND METHOD

2.1 Problem Definition

Economic load distribution relies on optimizing the fuel costs among the generation units to minimize fuel expenses for the requested loads. To calculate the optimal fuel cost for the power system, the mathematical definition of the fuel cost that each generator can demand needs to be formulated as a quadratic function, as shown in Equation (1) [19].

$$F(P_{Gi})_1 = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \ \$/\mathrm{h} \qquad (1)$$

2.2 IEEE 30-Bus Test System

In the optimization study, GWO and PSO algorithms were used to reduce fuel and ere; $F(P_{Gi})$ is the fuel cost, $a_{i,} b_i$ *and* $c_i$are the cost function coefficients for thermal unit i, and P_{Gi} is the active power generation of the i^{th} thermal unit. The cost function can be practically explained in more detail, especially in the case of steam turbines used in thermal power plants, where the opening and closing of steam valves can linearly increase or decrease the cost function. If the fuel cost function is to be expanded, taking into account the effects of the valve point loading of generator units, it can be rewritten as in Equation (2) [20].

$$F(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i + \left| e_i \sin\left[f_i\left(P_{Gi}^{min} - P_{Gi}\right)\right]\right| \qquad (2)$$

Here; e_i *and* f_i are the cost function coefficients for fuel type of unit ith reflecting valve-point effects and P_{Gi}^{min} is the minimum active power generation of thermal unit i. With the addition of valve loading points to this objective function, non-convex fluctuations will occur in the power versus generation cost curve. Overcoming these fluctuations becomes a challenge that needs to be addressed through optimization efforts. In economic power distribution cost optimization, some constraints such as transmission line losses, power flow limits, environmental emission gas values, and generator power limits need to be considered [21]. Among these constraints, the most critical is transmission line power losses. Strategies specified in Equations (3-4) are used to minimize transmission line losses.

$$P_{loss} = P_G^T B_{ij} P_G + B_{io} P_G + B_{oo} \tag{3}$$

$$P_G = [P_{G1} P_{G2} P_{G3} \ldots\ldots\ldots\ldots . P_{GN}]^T \tag{4}$$

Here; B_{ij}, B_{io} and B_{oo} are the coefficients of the power loss matrix. The power injected into the power system by generators must be equal to or greater than the sum of the demand power and the loss power. P_G represents the total power generated by all generators, and the total P_{loss} is used in calculating the magnitude of losses. Equation (5) defines the demand power (P_{load}) and loss power corresponding to the generated power for the entire power system [22].

$$\sum_{i=1}^{n} P_{Gi} \geq P_{load} + P_{loss} \tag{5}$$

The fundamental issue with fossil-fuel-based thermal power plants is that emissions gases remain as harmful by-products of fuels. Environmental sensitivity is increasing every day, and global efforts are underway to reduce greenhouse gases. The second-degree mathematical expression defined in Equation (6) explains the relationship between emission gases and power generation [23].

$$E(P_{Gi}) = a_{ei} P_{Gi}^2 + b_{ei} P_{Gi} + c_{ei} \tag{6}$$

Here, a_{ei}, b_{ei} and c_{ei} are the cost function coefficients for thermal unit i. Instability in the power system can arise when the total generated power is less than the demand power and total losses, leading to voltage and frequency instability conditions. The environmental objective function representing the emissions as a quadratic function of generation unit (P_{Gi}) can be defined as in Equation (7) [24]-[26].

$$F(P_{Gi})_2 = \sum_{i=1}^{n} \mu + \mu_1 \left(\sum_{i=1}^{n} (P_{Gi}) \right) + \mu_2 \left(\sum_{i=1}^{n} (P_{Gi} - (P_{load} + P_{loss}))^2 \right) \tag{7}$$

Here, μ, μ_1 and μ_2 are the emission gas and load balance weighting factors. n is the number of generation units. The optimization problem to minimize fuel cost and emissions can be formulated as in Equation (8) [27].

$$Minimize \ [F(P_{Gi})_1, F(P_{Gi})_2] \tag{8}$$

In the event that the expected solution cannot be reached in the realization of the economic power distribution objective function, these coefficients are used as determinative penalty coefficients. Each power generation unit is expected to operate within its own generation limits. When this condition is satisfied, the stability of the power system will have been fulfilled as the most important criterion. Equation (9) represents the minimum and maximum power generation range for each generator [26]-[28].

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \tag{9}$$

In addition to these considerations, it is crucial to determine the speed and load limits of generators during extra load acceptance and shedding. Ensuring that the transmitted power on power transmission lines does not exceed the maximum capacity of the transmission lines is valuable for the operational stability of the power system, allowing transmission lines to operate within their limits [29]. power losses on the IEEE 30-bus test system. Figure 1 shows the single-line diagram of the IEEE 30-bus test system used in the study.

This system consists of a total of 30 buses, including 29 connection buses and 1 swing bus. Buses 1, 2, 5, 8, 11, and 13 are generator buses [20], [21]. Additionally, the system has a total of 41 transmission lines, including 37 transmission lines and 4 transformer branches. The system reports a total active load of 283.34 MW and a reactive load of 126.2 MVAr [21].

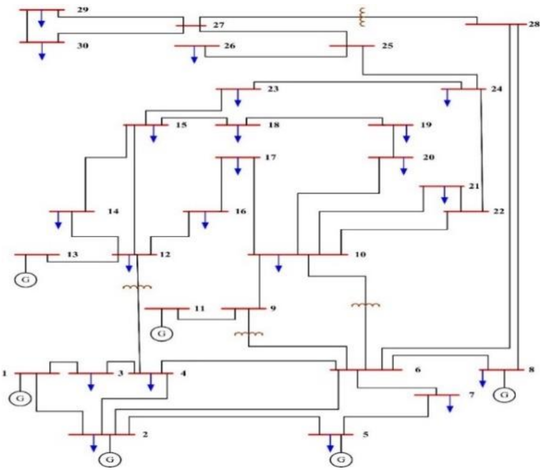

Figure 1: IEEE 30-bus system single line diagram.

2.3 *Metaheuristic Algorithms*

Metaheuristic algorithms are computational methods inspired by intuition and observations in nature. These algorithms are employed to solve complex and multi-dimensional optimization problems. Metaheuristic algorithms based on swarm intelligence are preferred in the restructuring of power systems and the optimization of fuel consumption and emissions in generation units, playing a significant role in solving power flow problems [22]-[27]. Optimization algorithms involved in tasks such as sensitivity analysis, location, and capacity determination, and the restructuring of power systems can produce different results in each run. Although they do not guarantee the best result, they are capable of achieving near-optimal results [28]-[32].

In this study, cost optimization has been conducted on the IEEE 30-bus test system data. During the optimization process, metaheuristic algorithms, specifically Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO), were employed to minimize the single-objective function outlined in Equation (7), subject to the constraints specified in Equation (8). Additionally, a simulation and test environment were designed on MATLAB to evaluate the effectiveness of PSO and GWO-based optimization processes developed to reduce the operating costs of power systems.

2.3.1 *Grey Wolf Optimization (GWO)*

The Grey Wolf Optimization (GWO) algorithm based on swarm intelligence was initially proposed by Mirjalili and Lewis in 2014 [33]. This algorithm is designed by drawing inspiration from the social behaviours exhibited by grey wolves during hunting. The interactions among three leader wolves, namely, Alpha, Beta, and Delta, and the rest of the pack are utilized to explore potential solutions in the solution space. Alpha represents the leader type, Beta is the second-ranking leader in the hierarchy, and Delta is the third-ranking leader in the pack, following Alpha and Beta leaders. Omega, consisting of the youngest or newest members at the lowest level of the pack, is responsible for following the other three leader types. The swarm intelligence-based hunting is carried out in four stages: searching for prey after forming the hierarchy, encircling, attacking, and hunting [16],[33]. Figure 2 illustrates the 2D and 3D hunting strategies of a wolf pack.

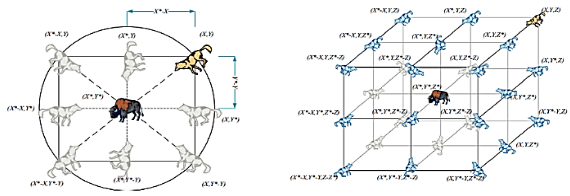

Figure 2: a) 2D, b) 3D hunting strategy of GW [33].

While Alpha and Beta represent the two potential best candidate solutions, Delta produces the third-best solution. The mathematical expressions used for the hunting, approaching the prey, and surrounding stages of Alpha, Beta, and Delta grey wolves are provided in equations (10-20) [33].

$$D = |C.Xp(i) - X(i)| \tag{10}$$
$$X(i + 1) = |Xp(t) - A.D| \tag{11}$$

Here; i represents the iteration number; $Xp(i)$ is the current position of the prey; A and C are coefficient vectors; D is the distance to the prey; and X represents the individual's position. Coefficient vectors A and C are calculated as shown in Equations (11) and (12), respectively.

$$A = |2a.r_1 - a| \tag{12}$$
$$C = |2a.r_2| \tag{13}$$

Here; the value of a is linearly decreased in each iteration between 2 and 0. r_1 and r_2 are random factors generated within the range [0, 1]. While the hunting strategy of wolf packs in 2 and 3-dimensional spaces, as represented in Figure 2, is illustrated, individuals in the search space move on a cube-sphere. The hunting tendencies of individuals are defined as follows [33].

$$D\propto = |C1.X\propto - X| \quad (14)$$
$$D\beta = |C2.X\beta - X| \quad (15)$$
$$D\delta = |C3.X\delta - X| \quad (16)$$
$$X1 = |X\propto - A1.D\propto| \quad (17)$$
$$X2 = |X\beta - A2.D\beta| \quad (18)$$
$$X3 = |X\delta - A3.D\delta| \quad (19)$$
$$X_{(t+1)} = \frac{X_1 + X_2 + X_3}{3} \quad (20)$$

According to the equations, the position information of the prey, which has three valid and valuable solutions obtained by the three leading individuals, is updated by combining the information brought by other herd members. As the value of the hunting agent a decrease, the position of the next iteration, approaching the prey, is determined in a better location than its previous position. The adapted flowchart of the grey wolf algorithm for power system optimization is shown in Figure 3.

2.3.2 *Particle Swarm Optimization (PSO)*

Particle Swarm Optimization (PSO) is another metaheuristic-based swarm intelligence optimization technique used in this study. This algorithm was first introduced by Kennedy and Eberhart in 1995 [34]. PSO is a mathematically modelled optimization algorithm inspired by the foraging behavior of living swarms such as fish and birds. In this mathematical model, each particle seeks the best solution for a function. While each particle has its own unique individual position, among the positions obtained by each individual in the swarm, the best position is defined as the global best position [10]. Each position is associated with a velocity vector. While the individual best position is denoted as P_{best} and the global best position in the swarm is denoted as G_{best} in this diagram, the velocity vectors forming the positions are given by the equations for the inertia and weight coefficients Equations (21-23) [34],[35].

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{iter_{max}}.iter\right) \quad (21)$$

$$v_{i,j(t+1)} = w\, v_{i,j(t)} + c_1 r_{1,j(t)}\left(Pbest_{i,j(t)} - x_{i,j(t)}\right) + c_2 r_{2,j(t)}\left(Gbest_{(t)} - x_{i,j(t)}\right) \quad (22)$$

$$x_{i(t+1)} = x_{i(t)} + v_{i(t+1)} \quad (23)$$

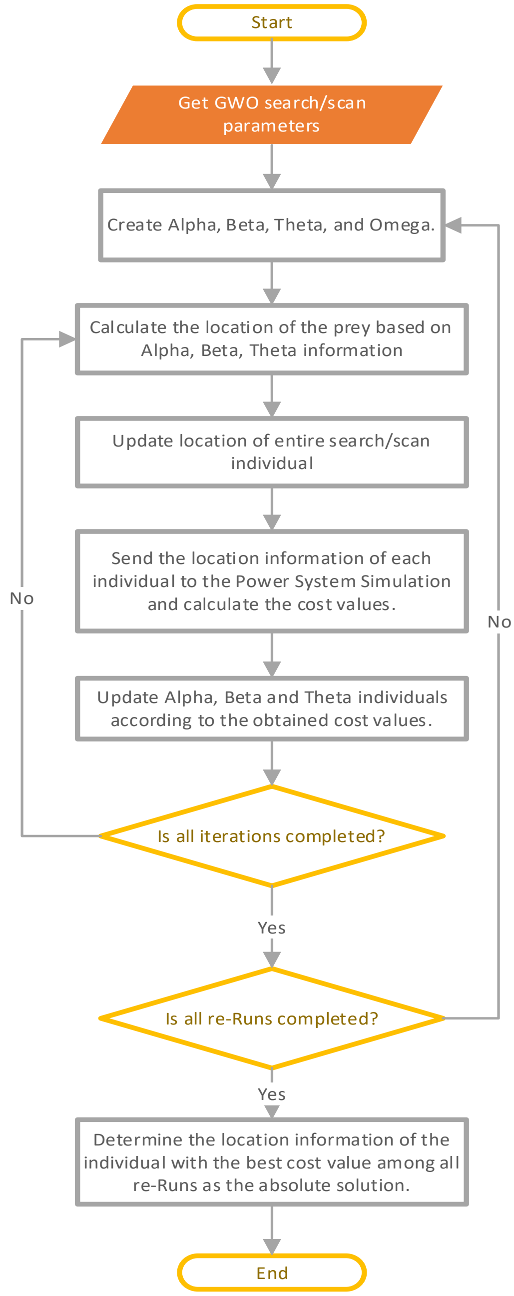

Figure 3: GWO flowchart.

Here; w is the inertia weight of the particle, $v_{i,j(t+1)}$ is the particle's next velocity, $x_{i(t+1)}$ is the particle's position, c_1 and c_2 are coefficients for approaching local and global best positions, and r_1 and r_2 are randomly generated factors for approaching values in the range [0-1]. The flowchart adapted for power system optimization using the PSO algorithm is shown in Figure 4.

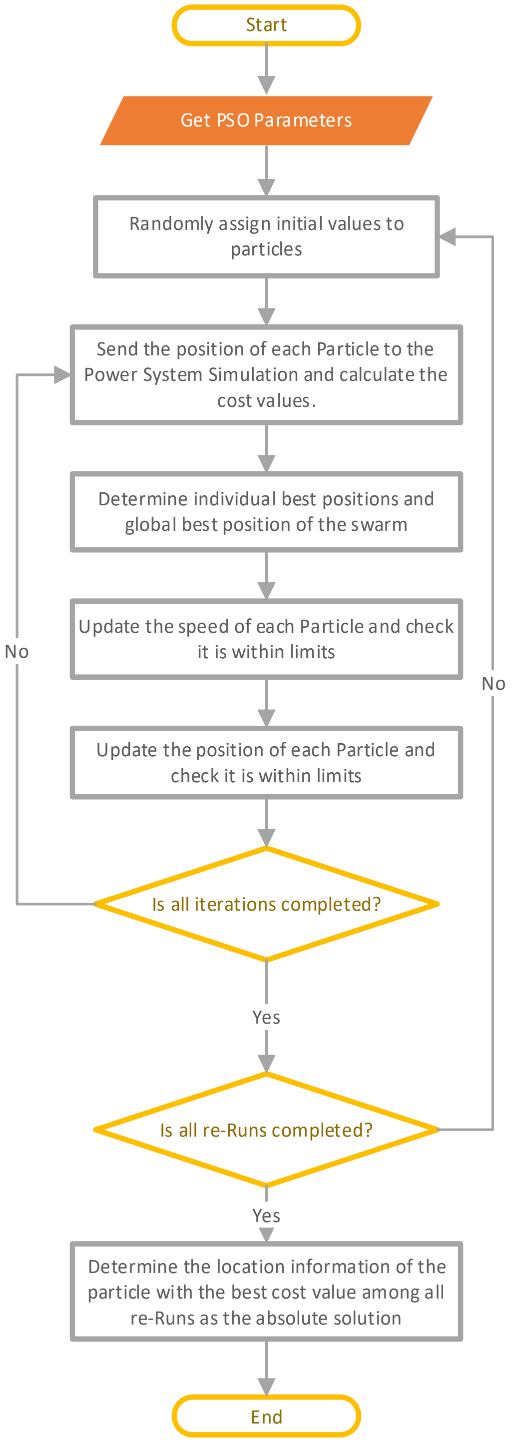

Figure 4: PSO flowchart.

3. OPTIMIZATION RESULTS

In the study with a defined single-objective function, simulations were performed using MATLAB R2020a software on a system with an Intel Core i5-3470 CPU, 3.20 GHz processor, and 6 GB RAM to conduct various tests for the optimization process. In all simulation and optimization processes, voltage limits at load buses were constrained to the range of 0.95-1.05pu. After determining suitable parameter values and population sizes for the GWO and PSO algorithms, each algorithm was run thirty times for 100 iterations with the selected parameters, and the obtained results were evaluated. In this study, significant differences were observed in the results when the population and the number of re-runs for the PSO and GWO algorithms were selected at three different values (20, 30, and 50). Therefore, the optimization results obtained for these values are presented in the study. Table 1 contains the parameters and their specified values for the optimization algorithms.

Table 1: Parameter values of algorithms.

GWO		PSO	
Iteration	100	Iteration	100
a	2	C1	2
a_0	2	C2	2
		W_{max}	0.9
		W_{min}	0.4
Population	20/30/50	Population	20/30/50
re-runs	20/30/50	re-runs	20/30/50

With the values specified in Table 1, the algorithms were individually run thirty times, and the average of the obtained results was calculated. In the initial study, the population size and the number of re-runs were set to 20 for both algorithms, and optimization was performed. The values obtained for the first case are presented in Table 2.

Table 2: Optimization results for the first case.

	GWO	PSO
Min ($/h)	808.207	805.843
Max ($/h)	1069.800	1191.000
Average ($/h)	993.444	990.103
Standard Deviation	18.011	55.999
Avg. Duration (Sec.)	27.659	27.850

According to these results, the PSO algorithm, producing a minimum hourly generation cost of $805.843, an average value of $990.103, and a standard deviation of 55.999, performed better than the GWO algorithm. However, it is observed that the standard deviation of the GWO algorithm is lower, meaning that its results are closer to each other. The average CPU usage times for the algorithms are quite close to each other, approximately 27 seconds.

As a result of the parameters obtained through the optimization of the two algorithms, a system simulation was conducted on the system whose block diagram is given in Figure 1. The power values generated, consumed, and lost in the system were obtained. The results are shown in Table 3. As seen in Table 3, the total power generated by the generators is 294.484 MW with the parameters obtained by PSO and 294.442 MW with the parameters obtained by GWO. When examining power losses, it is observed that the values obtained with GWO, with a loss value of 11.102 MW, stand out.

Table 3: Generator active power generation, consumption and loss values for the first case.

Bus	GWO P_G (MW)	PSO P_G (MW)
1	166.517	177.836
2	46.488	47.665
5	27.313	21.313
8	21.440	23.600
11	13.755	10.001
13	18.929	14.069
Total Power Generation	294.442	294.484
Total Power Consumption	283.340	283.340
Total Power Loss	11.102	11.144

In the second study, the population size and re-runs number for both algorithms were set to 30, and the optimization was repeated. Table 4 presents the performance values obtained after the optimization. Upon examination of this table, it is observed that, for PSO, the minimum hourly generation cost remains the same at $800.954, but the average value decreases to $968.141 compared to the initial condition. The standard deviation value is obtained as 6.470, depending on the increase in iterations. The average CPU usage time is determined to be 40.773 seconds. With this optimization, it is concluded that the PSO algorithm produces better results than GWO in terms of all values.

Table 4: Optimization results for the second case.

	GWO	PSO
Min ($/h)	804.537	800.954
Max ($/h)	1025.000	992.255
Average ($/h)	985.987	968.141
Standard Deviation	14.159	6.470
Avg. Duration (Sec.)	42.204	40.773

The system's operation with the parameters yielding the best objective function values obtained through optimizations and the resulting values for generation, consumption, and loss of power are presented in Table 5. In Table 5, the total power generated by generators with the parameter values obtained with PSO is 292.941 MW, while with the parameter values obtained with GWO, it is 293.225 MW. When losses are examined, it is observed that the PSO algorithm stands out with a loss value of 9.601 MW. When the first and second cases results are compared, it is observed that the increase in the population size and the number of runs does not reduce the operating cost and power loss values after 30 iterations.

Table 5: Generator active power generation, consumption and loss values for the second case.

Bus	GWO P_G (MW)	PSO P_G (MW)
1	171.670	177.605
2	48.745	48.929
5	21.354	22.158
8	20.764	21.663
11	16.815	10.439
13	13.877	12.147
Total Power Generation	293.225	292.941
Total Power Consumption	283.340	283.340
Total Power Loss	9.885	9.601

In the third study, the population size and iteration number were set to 50 for both algorithms, and the optimization and simulation processes were repeated. When Table 6 is examined, it is observed that the minimum hourly generation cost for PSO has decreased to $800.472, but the average value has decreased to $805.165 compared to the first two cases. It is noted that the standard deviation value has decreased slightly due to the increase in the number of individuals in the swarm and the number of iterations. Also, due to the increase in the swarm size and the number of iterations, the algorithm's computation times are increased. As seen in Table 6, in terms of computation times, the average CPU usage time of the GWO algorithm increases less compared to PSO, with 49.113 seconds. According to the performance criteria, it is observed that the results of PSO are better than GWO.

Table 6: Optimization results for the third case.

	GWO	PSO
Min ($/h)	803.340	800.472
Max ($/h)	853.105	825.441
Average ($/h)	820.082	805.165
Standard Deviation	11.729	5.243
Avg. Duration (Sec.)	49.113	79.024

For the third case, the generation, consumption, and loss power values obtained from running the system with the parameters obtained by optimization algorithms are presented in Table 7. In Table 7, when the parameters obtained by PSO are used, the total power generated by the generators is 292.344 MW, while when the parameters obtained by GWO are used, it is 292.471 MW. When losses are examined, it is observed that the PSO results are better with a loss value of 9.004 MW. Compared to the previous two conditions, it is evaluated that the increase in population size and the number of runs does not much reduce the operating cost and power loss values after 50 iterations.

Table 7: Generator active power generation, consumption and loss values for the third case.

Bus	GWO P_G (MW)	PSO P_G (MW)
1	167.975	178.193
2	52.104	48.496
5	22.203	21.976
8	19.846	21.645
11	16.565	10.007
13	13.778	12.027
Total Power Generation	292.471	292.344
Total Power Consumption	283.340	283.340
Total Power Loss	9.131	9.004

4. DISCUSSION

In the study, the total power generation and total power loss values obtained from three different optimizations are comparatively shown in Figure 5 for GWO and PSO algorithms. Since the total consumption in the system did not change, this value is not included in this graph. In Figure 6, the average hourly power generation costs obtained according to the results of the three cases and two optimization algorithms studied with different parameters in the study are presented comparatively.

The graph in Figure 6 shows both the efficiency of PSO and GWO algorithms in minimizing overall operating costs and the effectiveness of these metaheuristic algorithms in addressing the complex and dynamic nature of power systems. These visual reveals that the PSO algorithm gives better results than the GWO algorithm in all three cases in the study for optimizing the hourly power generation cost. According to these optimization results, the most cost-effective value of 800.47 $/h was reached in the simulation tests performed for the third case, where 50 population and re-Runs values of the PSO algorithm were used.

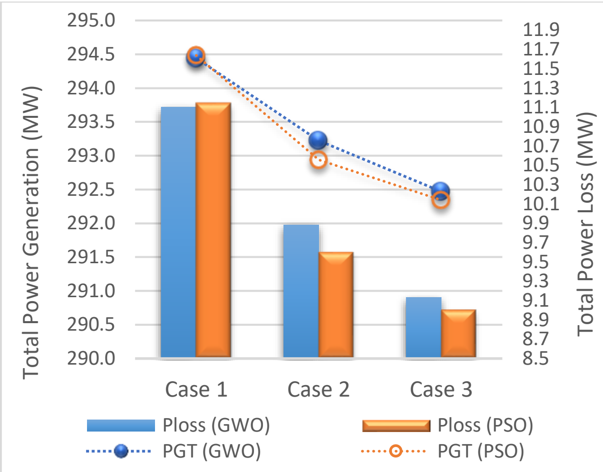

Figure 5: Total power generation and power loss.

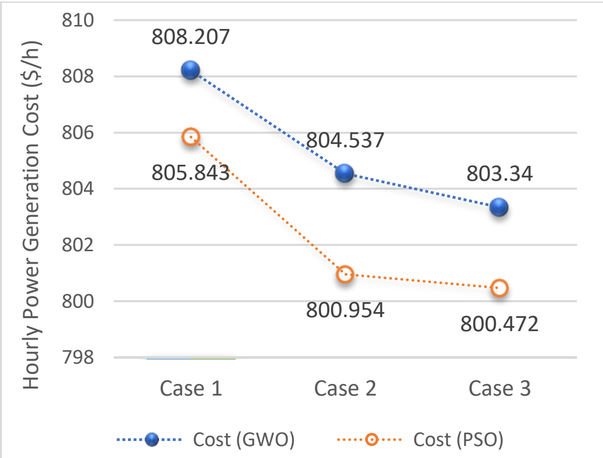

Figure 6: Hourly power generation cost.

Previous studies have investigated similar approaches using evolutionary and metaheuristic algorithms on the IEEE 30-bus test system, with their findings compared to the results of the present study in Table 8. The table evaluates the total power loss and generation cost resulting from running these algorithms on the IEEE 30-bus test system.

Table 8: Literature comparison.

P_G (MW) \ Buses	Algorithms Used in Previous Studies in the Literature				Proposed Algorithm	
	PS [36]	GA-PS [36]	EP-OPF [37]	ABC [38]	GWO	PSO
1	175.727	175.663	173.826	176.263	167.975	178.193
2	48.681	48.641	49.998	48.383	52.104	48.496
5	21.428	21.422	21.386	20.871	22.203	21.976
8	22.831	22.622	22.630	22.713	19.846	21.645
11	12.067	12.381	12.928	12.453	16.565	10.007
13	12.000	12.000	12.000	12.000	13.778	12.027
Total P_{loss} (MW)	9.335	9.329	9.368	9.283	9.131	**9.004**
Generation Cost ($/h)	802.015	802.014	802.556	801.721	803.340	**800.472**

One such study employing pattern search and genetic algorithms [36] concluded that these algorithms exhibited superior overall convergence performance, demonstrating competitiveness. In another study [37], it was demonstrated that the total generator fuel cost achieved through an evolutionary algorithm for economic power dispatch on the IEEE 30-bus test system was lower compared to costs incurred by evolutionary programming, tabu search, hybrid tabu search, simulated annealing, and enhanced tabu search, thus yielding significant savings in generator fuel costs. Furthermore, a study [38] utilizing the metaheuristic artificial bee colony optimization algorithm reported a minimum power loss value of 9.283 MW and an hourly generation cost of $801.721.

In Case 3 of this study, where the population number and the number of runs of the PSO algorithm are set to 50, it is observed that the application of the PSO algorithm yields promising results. With a minimum power loss value of 9.004 MW and a generation cost of $800.472/hour, the PSO algorithm demonstrates practicality and approaches the global optimum solution efficiently, exhibiting high convergence performance. The positive outcomes highlight PSO's capability to compete effectively with other algorithms [36]-[38], underscoring its robust search ability.

5. CONCLUSION

In this research, swarm intelligence-based PSO and GWO algorithms were applied to the optimization problem using the cost-oriented objective function for sustainable economy on the IEEE 30-bus test system. In this study, which aims to reduce the total power loss and system operating cost, the effects of algorithm parameters such as population and number of runs on the objective function and power loss results were examined through tests carried out in a simulation environment. Significant differences in the results were observed when the population and number of reruns were selected at values of 20, 30 and 50 for the PSO and GWO algorithms, respectively. As the population and number of runs increased, there was no significant change in the minimum values of the objective function, while a decrease was observed in the mean and standard deviation values. On the other hand, it was observed that there was an increase in total power loss values and average CPU usage times. In conclusion, the findings of the study show that swarm intelligence algorithms can be used effectively in power system optimization and that various parameter choices can have a significant impact on the results.

In this research, PSO and GWO algorithms were successfully applied to cost-oriented optimization problems and effective results were obtained in power systems. In the simulation tests conducted for the third case, where the PSO algorithm used 50 population and rerun values, it was determined that it reached the most appropriate operating cost value of 800.47 $/Hour. It is evaluated that in the future, studies focusing on multiple targets using different objective functions may help to improve power systems more comprehensively. Thus, processes that take an approach that includes reliability, sustainability and other elements as well as operational costs can emerge. Additionally, examining new parameter selections or improved variations to increase algorithm performance can be among the studies that can contribute to the field. Although the IEEE 30 bus test system serves as a standard benchmark, future research involving distributed generation systems may extend the analysis to suit larger, more complex power systems. It has been evaluated that such studies have a significant potential in increasing the efficiency of power systems and minimizing operating costs.

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