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OPF Solution by the Hunger Games Search (HGS) Algorithm

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Abstract: Optimal power flow (OPF) is a significant problem in electrical engineering. The optimization method of the Hunger Games Search (HGS) algorithm was presented in this study, which finds the OPF under different case studies. These cases include reducing the total fuel cost, minimizing power losses in transmission lines, reducing the amount of pollutants generated by units, and minimizing voltage variation at load buses. MATLAB software was used to test the suggested algorithm using the IEEE 30-bus power system. The findings indicate that the suggested algorithm was effective in accomplishing the goals of obtaining a reduction of 11.30% in the use of fuel cost, a reduction of 46.90% in power loss, a reduction of 88.11% in voltage fluctuation, and a reduction of 3.38% in pollutants while simultaneously satisfying all of the restrictions. We compared the used and published optimization methods. Finally, the HGS presented good performance in terms of power loss and fuel cost compared with other techniques.

Keywords: Hunger Games Search, power flow, fuel cost, emission, power system, MATLAB.

饥饿游戏搜索(人类地质调查局)算法的 OPF 解决方案

摘要：最佳功率流（OPF）是电气工程中的一个重要问题。本研究提出了饥饿游戏搜索（人类地质调查局）算法的优化方法，在不同的案例研究下找到 OPF。这些案例包括降低总燃料成本、最大限度地减少输电线路的功率损耗、减少机组产生的污染物量以及最大限度地减少负载母线的电压变化。MATLAB 软件用于使用 IEEE 30 总线电力系统测试建议的算法。结果表明，该算法有效实现了燃料使用成本降低 11.30%、功率损耗降低 46.90%、电压波动降低 88.11%、电压波动降低 3.38%的目标。%的污染物，同时满足所有限制。我们比较了已使用和已发布的优化方法。最后，与其他技术相比，人类地质调查局在功率损耗和燃料成本方面表现出了良好的性能。

关键词：饥饿游戏搜索、潮流、燃料成本、排放、电力系统、MATLAB。

1. Introduction

The optimal power flow (OPF) is an optimization problem that involves determining the optimal values for control variables, such as generator output levels and transformer tap ratios, in electric power systems (EPS) [1, 2]. The aim is to schedule these variables while satisfying the system's constraints and maintaining reliability and security. The goal of OPF is to minimize the overall cost of generating and transmitting electricity, which encompasses various expenses, including fuel, maintenance, and operational costs, while also meeting the system's demand [3]. OPF constraints can be classified into two types: equality and inequality constraints. Power balance equations are examples of equality constraints that enforce the condition that the amount of power injected into the system is equal to the amount of power consumed [1]. In OPF, inequality constraints restrict decisions and dependent variables to operating within allowable boundaries, such as generator output and transmission line capacity. Solving the OPF problem is challenging because of its non-linearity and complexity. Various conventional optimization methods, including Newton's method, the gradient projection method, and the interior point method, have been developed to solve the OPF problem [4, 5]. However, these methods have limitations, such as the need to linearize the objective function and constraints, which can impact the final solution. In addition, the economic dispatch (ED) problem is made even more difficult by the requirement that it must simultaneously optimize the power output of multiple generators, each of which has different cost and emission characteristics, while adhering to transmission and operational constraints, such as ramp rate limits, generation limits, and reserve requirements [6-8]. This is a particularly difficult problem to solve because it requires optimizing the power output of multiple generators at the same time. The goal is to reduce the total cost of producing electricity as much as possible. This cost metric considers not only the price of fuel connected to each generator but also the environmental costs associated with emissions [9, 10].

In recent years, several techniques have been used to obtain OPF and ED solutions in standard power systems and minimize active power losses. In [11], Moth Swarm Algorithm (MSA) and Gravitational Search Algorithm (GSA) were integrated to create a hybrid strategy for power systems that use wind energy sources. The test scenarios, both with and without wind power, are considered for resolving the goal functions of decreasing the fuel cost for increased power efficiency. Moreover, the findings of the simulation are tested using the IEEE 30 bus, IEEE 57 bus, and IEEE 118 bus, both with and without wind power. Compared with the conventional methods, the MSA–GSA algorithm that was developed provides much improved outcomes.

[12] presented an updated version of the JAYA algorithm to solve the problem of OPF while considering renewable energy sources (RES). The algorithm has four distinct objective functions, which reflect a reduction of fuel cost, pollutants electrical transmission loss, and enhancement of the voltage distribution. It is possible to develop the suggested modified JAYA (MJAYA) method by adjusting the formula used to revise the answers depending on the best and worst solutions.

[13] proposed a hybrid optimization approach for solving multi-objective optimum power flow problems (MO-OPF) in a power system. The combination of algorithms that has been given the name DA-PSO integrates the structure of two different optimization strategies—namely, the dragonfly algorithm (DA) and particle swarm optimization (PSO)—to locate the optimum solutions for the power network. To address the MO-OPF issue, the hybrid method was constructed. The reduction of fuel costs, pollutants, and losses during transmission was the overarching goal of the OPF's objective functions.

In [14], the OPF issue in a wind-thermal power system known as the multi-objective optimum power flow (MO-OPF) problem was studied. In this case, the Glowworm Swarm Optimization (GSO) method is used to solve issues involving a single optimization goal, while the multi-objective GSO (MOGSO) approach is used to tackle problems involving a multi-optimization function. On a modified version of the IEEE 30 and 300 bus test systems, the suggested optimization issue is handled using wind farms situated at various buses within the system.

In [15], an improved technique based on multi-area ED was used. MAED is a critical issue that has to be solved to distribute power production via dispatch techniques to reduce the amount of money spent on fuel. Within the framework of economic dispatch, this power production distribution must always comply with the restrictions of the production limit, transmission line, and power balance. It is impossible to find a solution to MAED using traditional methods because it is a problem that is both complicated and nonlinear. The solution of economic dispatch issues has been approached using various metaheuristic approaches.

In [16], the authors demonstrated an application of one of the most recent swarm intelligence algorithms called the gray wolf optimizer (GWO). This method is used to solve economic dispatch issues that are nonlinear, non-convex, and discontinuous. These problems also include several equality and inequality requirements. GWO is a novel metaheuristic algorithm that is only tangentially inspired by the actions of grey wolves. To improve its effectiveness, the optimizer has been modified to include both crossover and mutation. Four ED issues with forbidden operating zones, valve position loading impact, and ramp rate limit limitations were addressed, with and without transmission losses.

In this study, a highly efficient HGS algorithm was used to find the OPF under different case studies. The main contributions of this research are as follows:

- Solving single- and multi-objective OPFs using HGS;
- The issues of traditional algorithms such as PSO and JAYA are addressed and solved by suggesting HGS for OPF in different case studies;
- Applications to the IEEE 30-bus system for different case studies are done. Because of this, the capacity of the HGS has been accomplished.

1.1. Criteria for Selecting the Hunger Games Search Algorithm (HGS) in OPF

The decision to deploy the HGS for our research emerged from a series of preliminary studies and considerations. The inherent characteristics of HGS, inspired by the behavior of social animals when foraging, presented a unique approach to addressing the OPF challenge. The ability of the HGS to mimic the influence of hunger on activity levels offers a dynamic search process that adapts to different challenges and constraints of the OPF problem, making it a potentially powerful tool. When compared with existing algorithms such as the MSA, GSA, and PSO, it was observed that while they offer commendable results, certain challenges such as scalability, adaptability, and efficiency in specific scenarios make them less ideal for some OPF problems. In our preliminary studies, the HGS demonstrated the potential to bridge these gaps, which drove our interest in exploring it further.

2. Problem Formulation

The OPF solution is typically described as an N-linear optimization solution. The mathematical equation of the OPF problem can be represented as follows [1-4]:

$$X^T = [P_{Gslack}, V_{L1} .. V_{LNPQ}, Q_{G1} .. Q_{GNG}, S_{l1} .. S_{1NTL}] \quad (1)$$

The state vector denoted by X^T includes various quantities such as the active power of the slack bus (P_{Gslack}), magnitude of the voltage on the load buses (V_{LNPQ}), reactive power of the generators (Q_{GNG}), and apparent power S_{1NTL}, where NPQ is the number of PQ buses, NG - the number of generators, and NTL – the number of transmission lines [2]. The variable control vector of the OPF can be expressed as

$$u^T = [P_{G1}, P_{G2} \ldots P_{GNG}, V_{G1}, V_{G1} \ldots V_{GNG}, T_1 .. T_{NT}] \quad (2)$$

where P_{GNG}, V_{GNG}, T_{NT}, and NT are defined as the active power output of the generators except at the slack bus, the terminal voltage magnitude of the generators and the transformer tap ratio and the number of taps regulating transformers, respectively [2].

2.1. Objective Functions

In this paper, different objective functions based on the HGS algorithm are presented as follows:

The first objective function is fuel cost minimization for power generation optimization. Therefore, the goal is to minimize the overall cost of fuel required to generate power, which is represented by a quadratic function. Thus, the objective function is expressed accordingly [3]:

$$F_{FC} = \sum_{i=1}^{NG} a_i P_{Gi}^2 + b_i P_{Gi} + c_i \quad (3)$$

where i, bi, ci represent the fuel cost coefficients of a particular generator i^{th}.

The objective function for minimizing real power loss can be represented by the following equation [17]:

$$F_{LOSS} = \sum_{i=1}^{nl} \sum_{j \neq 1}^{nl} G_{ij} [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)] \quad (4)$$

In addition, in this research, minimizing emissions in power generation was obtained. However, burning fossil fuels in thermal power plants releases harmful pollutants like Sulphur oxides SOx and Nitrogen oxides NOx, posing a threat to the environment. To safeguard the environment, reducing emissions is crucial, and minimizing total emissions is an important goal in operating the PS. As air pollution becomes a mounting issue, more nations are placing greater emphasis on protecting the environment, which can be described as follows [7, 17]:

$$F_{Em} = \sum_{i=1}^{N_{gn}} \alpha_i P_{Gi}^2 + \beta_i P_{Gi} + \gamma_i \quad (5)$$

where αi, βi, and γi are coefficients that determine the level of emissions produced by the ith generator.

However, minimizing VD from 1.0 per unit is essential to improve the voltage profile at load buses, which is crucial for ensuring secure operation and high voltage quality. The objective function, which includes the load bus VD to achieve a desirable voltage profile, can be expressed as

$$V_D = \sum_{i=1}^{NP} |v_i - 1| \quad (6)$$

The equation computes V_D as a mathematical function of the aggregate count of PQ nodes (NP) and a normalized value of 1.0.

Furthermore, improving voltage stability (VS) through index minimization can be done based on the suggested HGS. The VS index (L-index), which is a measure of power network stability, ranges from 0 to 1. A high L-index value indicates a stable power transmission system, whereas a low value suggests the possibility of voltage collapse [4]. The L-index can be minimized to enhance VS, which is a significant concern associated with the level of loading and reactive power support. The L-index is commonly used to assess VS and can vary from 0 to 1 at any load bus [5].

2.2. Constraints in System Optimization

The optimization of objective functions is constrained by a set of conditions that restrict the possible solutions that meet the given requirements while optimizing the objective function. These constraints can be divided as follows:

2.3. Equality Constraints

The real power balance constraints can be expressed as follows:

$$\sum_{i=1}^{NB} (P_{Gi} - P_{di}) - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \cos\theta_{ij} + G_{ij} \cos\theta_{ij}\right] \quad (7)$$

The reactive power balance constraints can be written as

$$(Q_{GI} - Q_{DI}) - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \sin(\theta_{ij}) + B_{ij} \sin(\theta_{ij})\right] \quad (8)$$

2.4. Inequality Constraints

A set of constraints representing both the operational and physical limitations of a system, including the control and state variables, is as follows:

$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}$, i = 1,…..NG (9)

$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max}$, i = 1,…..NG (10)

$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}$, i = 1,…..NG (11)

$T_i^{min} \leq T_i \leq T_i^{max}$, i = 1,…..NG (12)

Therefore, the state variables can be presented as

$V_{L_i}^{min} \leq V_{L_i} \leq V_{L_i}^{max}$, i = 1,...,NL (13)

$Q_{G_i}^{min} \leq Q_{G_i} \leq Q_{G_i}^{max}$, i = 1,...,NL (14)

$P_{Gs}^{min} \leq P_{Gs} \leq P_{Gs}^{max}$, i = 1,…..NG (15)

3. The Hunger Games Search Algorithm

The HGS algorithm is a powerful population-based optimizer that uses randomized elements to explore and exploit complex landscapes effectively. Its adaptive and time-varying mechanisms enable it to handle multiple and local problems more efficiently [18, 19].

One of the key strengths of HGS is its flexibility, which allows it to adapt its performance to the fitness landscape by considering factors such as the percentage of hunger and the effect of hunger on the activity range. HGS uses individual fitness values to consider information when changing its behavior, which enables it to fully explore the solution space and enhance its diversification capability. It can develop search agents based on both the best and normal solutions, allowing it to explore a wider range of hidden areas in the feature space. The structure and logic of HGS are straightforward, which makes it easy to integrate with other evolutionary mechanisms. HGS outperforms both basic and advanced methods for scaling problems. The proposed HGS algorithm begins by initializing individual parameters and positions to achieve incremental intensification and enhance diversification.

The fitness of all individuals was calculated, and the HGS algorithm was applied to update their positions by generating a random number with a predetermined fixed value. When the generated random values are less than or equal to a specific constant value, the best solution is used to form a singleton. However, when the generated random value is greater than the predetermined fixed value, this process continues until the termination condition, i.e., the maximum number of iterations, is met, allowing the HGS algorithm to achieve the best possible result [7, 20].

The HGS algorithm emulates the behavior of hungry individuals in a social animal context as they search for food. The algorithm uses the variable "hungry (i)' to represent the hunger level of each individual. In every iteration, the hunger level of the best individual is set to 0, while the hunger level of the rest increases based on a formula that considers their fitness value, the best and worst fitness achieved in the current iteration, and the limits of the feature space.

The hunger sensation is restricted to a lower bound that influences the individual's range of activity through two formulas, $W_1(i)$ and $W_2(i)$. $W_1(i)$ accounts for the individual's hunger level, the number of individuals, and two random numbers, while $W_2(i)$ considers the absolute difference between the individual's hunger level and the sum of all individuals' hunger levels, a random number, and a constant factor. If an individual's fitness value equals the best fitness, its hunger level is set to 0; otherwise, it increases by the value of the hunger sensation. The parameter setting experiment discusses the value of the lower bound.

$(t+1) = \{Game1: X(t) \cdot (1 + randn\,(1)),\ r1 < l$ (16)

$Game2: W1 \cdot Xb + R \cdot W2 \cdot |Xb - (t)|,\ r1 > l,\ r2 > E$ (17)

$Game3: W1 \cdot Xb - R \cdot W2 \cdot |Xb - (t)|,\ r1 > l,\ r2 < E$ (18)

4. Results and Discussion

This study employs an artificial HGS to tackle the OPF problem in an IEEE-30 network, and it compares the findings with those of alternative optimization techniques. The network comprises six power generating stations, 4 transformers, and 41 transmission lines, as depicted in Fig. 1.

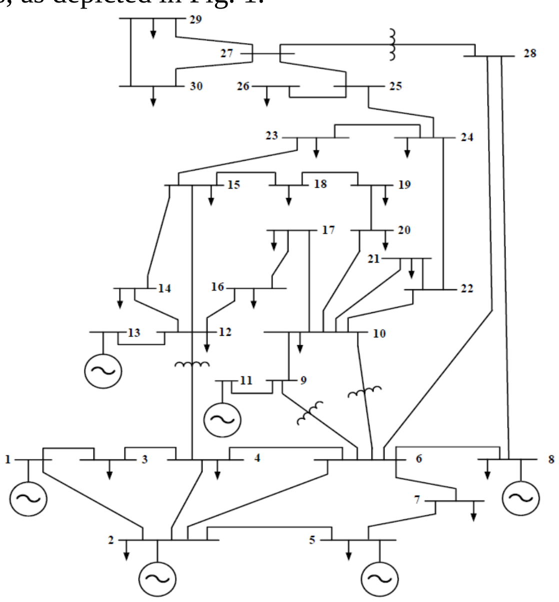

Fig. 1 Single-line diagram of the IEEE 30-bus test system [21]

To verify the performance of the proposed HGS method, MATLAB software was used to test the IEEE 30-bus system with different case studies. The obtained results are compared with those of the other authors in terms of real power losses, minimum fuel cost amount, voltage deviation, etc.; the used cases are as follows:

Case #1: Reducing overall fuel costs and emissions to the greatest extent possible;

Case #2: Reduction of fuel costs associated with fuel use and power losses;

Case #3: Minimization of fuel expense and voltage deviation;

Case #4: Minimizing the cost of gasoline while maintaining a constant voltage index;

Case #5: Reduction of effective power losses and emissions.

Fig. 2 shows the rapid convergence of the optimal solution to determine the optimal values or minimize the total fuel cost of power generation. The HGS approach reduced the cost from $901.6391 per hour to $799,386 per hour, with an 11.34% reduction compared with the initial state. The proposed approach was compared with other techniques, and it was found that the suggested technique is more efficient than conventional methods in terms of fuel cost reduction. Fig. 3 shows the fitness values of the real power losses vs. iterations. Fig. 4 and 5 show the emission amount and voltage deviation vs. iterations, respectively. Fig. 2 displays the system voltage stability obtained using the HGS algorithm for all cases. As shown in this figure, Case 5 shows the best solution for the voltage profile in this condition, while the worst case in terms of voltage amplitude is in the second case.

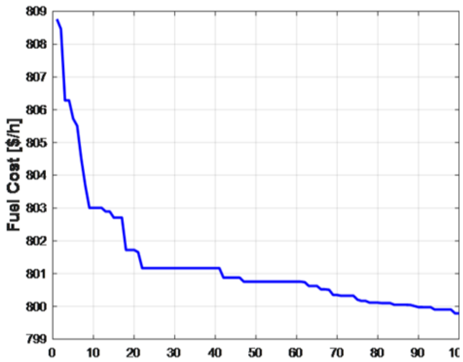

Fig. 2 Fuel cost objective function

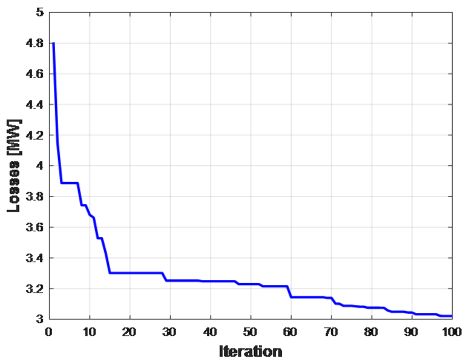

Fig. 3 Convergence response for power loss’s objective function

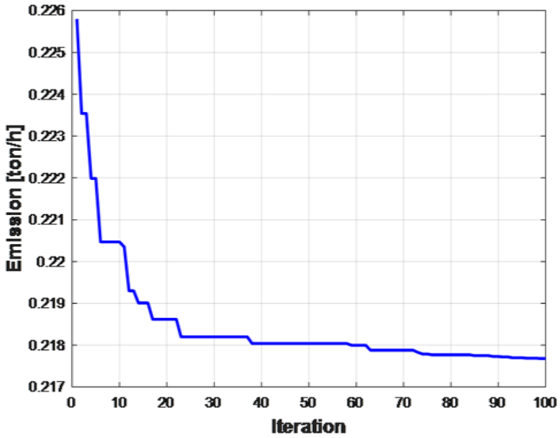

Fig. 4 Convergence curve for emission function

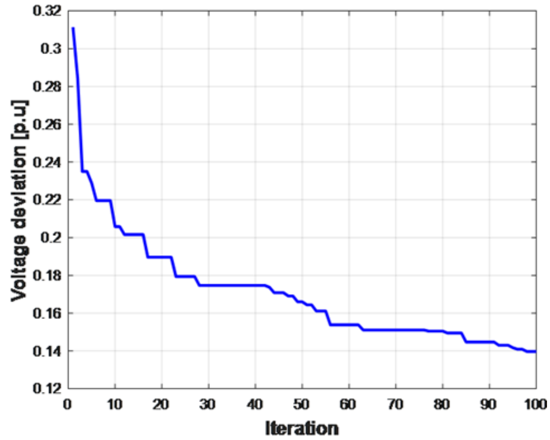

Fig. 5 Convergence plot for voltage deviation function

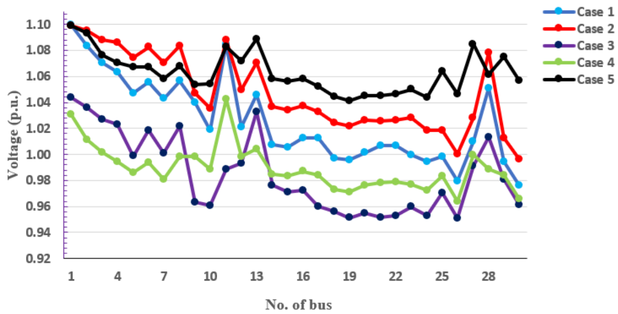

Fig. 6 The system voltage stability

Table 1 shows the obtained results for the IEEE 30 bus using the HGS algorithm. The used cases are obtained in terms of real power losses, emissions, volatge index (VD), and minimum fuel cost. The findings indicate that the suggested algorithm was effective in accomplishing the goals of obtaining a reduction of 11.30% in the use of fuel cost and a reduction of 46.90% in power loss.

Table 1 The obtained results using HGS

Case	Fuel cost ($/h)	Power loss (MW)	Emission (ton/h)	VD (p.u)
Initial	902	5.69	0.23	0.8244
Case #1	799.79	8.7799	0.3661	0.8244
Case #2	961.07	3.0207	0.2204	1.0303
Case #3	937.49	3.8545	0.2177	0.6058
Case #4	822.01	7.9329	0.3212	0.1397
Case #5	841.1	5.9155	0.2704	1.7127

A comparison of various optimization techniques in terms of fuel cost, emission, losses, real power losses, and voltage deviation is presented to show the performance of the HGS.

Table 2 compares different optimization algorithms and their corresponding results for real power losses for each performance metric. It is observed that some algorithms show significant improvement in certain metrics, whereas others perform better in other metrics. The presented HGS provides a good loss reduction of 3.027 MW. As a result, the selection of the most suitable algorithm depends on the specific requirements of the power system. Table 3 compares the HGS and recently published algorithms in terms of fuel cost. This comparison provides valuable insights into the performance of various optimization techniques and serves as a guide for researchers and practitioners to choose the most appropriate algorithm for a particular application. In this work, the algorithm used maintains a minimum fuel cost of 799.79 $/h, which is the best algorithm in this term compared with other techniques.

Table 2 Comparison between the HGS and recently published algorithms in terms of active power losses

Algorithm	**Power loss (MW)**	**Algorithm description**
Initial	5.69	-
HFPSO [2]	2.9473	Hybrid firefly and particle swarm optimization
JAYA [7]	3.1035	Jaya Algorithm
CS-GWO [18]	3.0861	Crisscross search-based gray wolf optimizer
ARCB [19]	3.1156	Adaptive real coded biogeography
MFA [20]	3.1005	Moth-Flame Algorithm
SCA [22]	2.9425	Sine Cosine Algorithm
IPSO [23]	5.07	Improved particle swarm optimization
HGS (Developed by the authors)	3.027	-

Table 3 Comparison between the HGS and recently published algorithms in terms of voltage stability (VSI)

Algorithm	**VSI (p.u)**	**Algorithm description**
Initial	0.23	-
HFPSO [2]	0.1037	Hybrid firefly and particle swarm optimization
JAYA [7]	0.124	Jaya Algorithm
CS-GWO [18]	0.1030	Crisscross search-based gray wolf optimizer
ARCB [19]	0.137	Adaptive real coded biogeography
MFA [20]	0.139	Moth-Flame Algorithm
IPSO [23]	0.1037	Improved particle swarm optimization
HGS (Developed by the authors)	0.1157	-

Table 4 compares the HGS and recently published algorithms in terms of emissions. The HGS presented an acceptable value of emissions, 0.2177 ton/h. The MGO algorithm presented the best solution of 0.20259 ton/h, while the other algorithms presented a value close to this value.

Table 4 Comparison between the HGS and recently published algorithms in terms of fuel cost

Algorithm	**Fuel Cost ($/h)**	**Algorithm Description**
Initial	901.64	-
HFPSO [2]	803.6002	Hybrid firefly and particle swarm optimization
JAYA [7]	832.4112	Jaya Algorithm
CS-GWO [18]	799.9978	Crisscross search-based gray wolf optimizer
ARCB [19]	800.6412	Adaptive real coded biogeography
MFA [20]	800.5099	Moth-Flame Algorithm
IPSO [23]	800.102	Sine Cosine Algorithm
HGS (Developed by the authors)	801.97	Improved particle swarm optimization
HFPSO [2]	799.79	-

Table 5 compares the HGS and recently published algorithms in terms of voltage stability (VSI).

Table 5 Comparison between the HGS and recently published algorithms in terms of emissions

Algorithm	**Emissions (ton/h)**	**Algorithm description**
Initial	0.3661	-
ARCB [19]	0.2048	Adaptive real coded biogeography
MFA [20]	0.20482	Moth-Flame Algorithm
SCA [22]	0.295	Sine Cosine Algorithm
IPSO [23]	0.2058	Improved particle swarm optimization
DEA [24]	0.20482	Differential evolution algorithm
MGO [25]	0.20259	Modified grasshopper optimization
AHA [26]	0.2042	Self-adaptive heuristic algorithm
HGS (Developed by the authors)	0.2177	-

The obtained simulation results show that the HGS has a good response and high robustness. Furthermore, the HGS approach is compared with other previously reported methods, confirming its effectiveness and superiority in solving OPF problems in terms of solution quality. It is noteworthy that HGS outperforms well-known methods such as JAYA and IPSO. The results obtained from the HGS algorithm provide valuable insights into its potential application in power flow optimization problems.

5. Conclusion

In this research, a HGS algorithm has been designed, developed, and effectively applied to an IEEE 30-bus power system under a wide variety of energy flow optimization problems while adhering to a variety of distinct constraints. First, the HGS algorithm has been studied in mathematical terms on the example of behavior of social animals in foraging; for this reason, the hunger levels used in the algorithm simulate the impact that hunger has on an individual's level of activity. MATLAB software was used to test the performance of the HGS under different case studies. The comparison between the recently published optimization techniques and suggested algorithm was done in terms of fuel cost value, voltage stability, power losses, and rate of emissions. Finally, the HGS method was effectively utilized to determine the best values for the control variables and achieve good results in terms of power losses of 3.0207 MW and fuel cost of 799.79 $/h.

5.1. Academic Contribution

The principal academic contribution of this study lies in presenting the HGS as a formidable tool for addressing OPF problems in electrical engineering. By juxtaposing it against existing methods, this study broadens the toolkit available to researchers and professionals, offering a novel and efficient approach that takes inspiration from natural behaviors. Such a biomimetic approach, although explored in other domains, remains relatively untouched in power flow optimization, making our research both innovative and original.

5.2. Limitations and Future Research

Although the results are promising, they are primarily based on the IEEE 30-bus power system, and the algorithm's efficacy in larger or more intricate systems remains an avenue for future studies. The simulations, though comprehensive, are bound by MATLAB's capabilities and might not fully encapsulate real-world intricacies. It is also possible that in specific scenarios, traditional algorithms might offer certain advantages over the HGS. Given these limitations, future research should aim to expand the application of HGS to more intricate systems and possibly merge its capabilities with other established algorithms to harness combined strengths. Furthermore, real-world applications and trials could be pursued to better gauge the practicality and scalability of our findings.

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