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Improved Firefly Algorithm for Optimum Power Loss In Smart Grids

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Abstract
The electricity networks, which operate in almost the same way since Tesla, have become unable to respond to the needs of the 21st century. The use of information technologies in electricity generation, transmission and distribution technologies is inevitable to meet the needs of today's networks adequately and provide uninterrupted energy. Smart grid systems have been established by integrating today's computer and network technologies into electricity networks. Adaptive, responsive, cost-effective, simultaneous and other electrical power systems can be connected to every point of the electricity network. This constitutes the basic backbone of the smart grid structure. Smart grid optimization is to ensure optimal power distribution between busbars without exceeding the physical limits of existing devices in the networks. In this article, an improved firefly algorithm is used to optimize power loss in the smart grid. The active and reactive power sum in the network has been optimized with the help of the firefly algorithm. The program written in Matlab GUI was applied to the IEEE30-busbar test system and the results were compared with the other meta-heuristic algorithms. The results obtained from the firefly algorithm were found to be more optimized compared to other algorithms.
Keywords: *Smart grid, optimization, Improved firefly algorithm, IEEE30-busbar system.*

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I. INTRODUCTION

Increased electricity demand and insufficient energy production and transmission enable power system networks to operate under unstable conditions. When the power system is operated under unstable conditions, the safety of the system is threatened and may cause voltage to unbalance. Today, while the power system is planning and operation, active and reactive power distribution are affected by voltage unbalance. Under overload conditions power system will be unsafe conditions due to deficient reactive power or not optimized reactive power flow [1]. The issue can greatly be solved when reactive power flow is reallocated. To increase stability in the power system, system losses can be minimized by providing optimum reactive power flow. A large amount of reactive power flow in an electrical power system is called actual power loss in the system. Therefore, to minimize actual power loss, optimized reactive power flow (ORPF) must provide across the lines, reactive power optimization is a long-standing issue for improving voltage balance by minimizing actual power loss [2]. Optimal Power Flow (OPF) is one of the power system planning that helps operators operate the system in the best way possible under certain restrictions. OPF can be applied periodically to minimize total fuel cost, reduce actual power loss and improve voltage stability.

For the economical safe and operation of power systems, ORPF is an important tool [3]. In ORPF, the network active power loss is reduced and the voltage profile is improved while performing a series of work and physical constraints. The reactive power flow is optimized by adjusting the values of the control parameters accordingly. Until recently, classical optimization methods have been used for this purpose. To solve the ORPF problem, techniques such as nonlinear programming [4] and gradient-based optimization algorithms are used. However, these methods have great disadvantages such as large numerical repetition and insufficient convergence properties and this will also provide greater calculation and greater response time. Newly developed meta-heuristic and swarm-based algorithms perform better than traditional methods. These algorithms are more preferred for power system optimization. These techniques are heuristic and swarm-based algorithms. Genetic algorithm [5]**,** particle swarm algorithm, artificial bee colony algorithm [6], cuckoo optimization algorithm [7], ant lion optimization and firefly algorithm [8] are examples of these methods. In the literature, studies to optimize power loss are given in Table 1.

The optimal load flow problem has more optimum results when it was applied to smart grid systems. The smart grid is often used to describe many different features in modern power systems that are directed to provide a cost-effective, reliable and sustainable electricity source [9]. In this vision, smart transmission lines, smart control centers, and smart transformer centers are considered as integrated systems that occur in the coaction of intelligent ingredients.

Table 1. Optimum power loss studies in the literature

Reference	Using Algorithm	Objective	Power system
[10]	MFO	Power loss, minimum voltage deviation	IEEE30, IEEE57, IEEE118-busbar system
[11]	FAPSO	Power loss,voltage deviation and voltage stabiliy index	IEEE30, IEEE118-busbar system
[12]	ALO	Power loss	IEEE30, IEEE57, IEEE300-busbar system
[13]	CLPSO	Power loss and voltage profile	IEEE30, IEEE118-busbar system
[14]	BBO	Power loss and voltage profile	IEEE30, IEEE118-busbar system
[15]	IEP	Power loss	IEEE118-busbar system and a power system in China

MFO [10]: Moth-flame optimization
FAPSO [11]: Fuzzy adaptive particle swarm
ALO [12]: Ant Lion optimization
CLPSO [13]: Comprehensive learning particle swarm optimization
BBO [14]: Biogeography based optimization
IEP [15]: Improved hybrid evolutionary programming

The smart grid concept is naturally associated with the integration of significant levels of Distributed Energy Source (DER) into the grid, including distributed energy sources, demand-side management [16], energy storage devices and other energy sources. The smart grid uses two-way electrical and information flow between consumers and the grid. The most important features of smart grids are: Enhancing renewable resources usage, reducing transmission and distribution losses and decreasing energy costs for customers, reduction of electricity consumption, ensure that consumers and electricity companies control demand. Fig 1 shows the conceptual model of the smart grid.

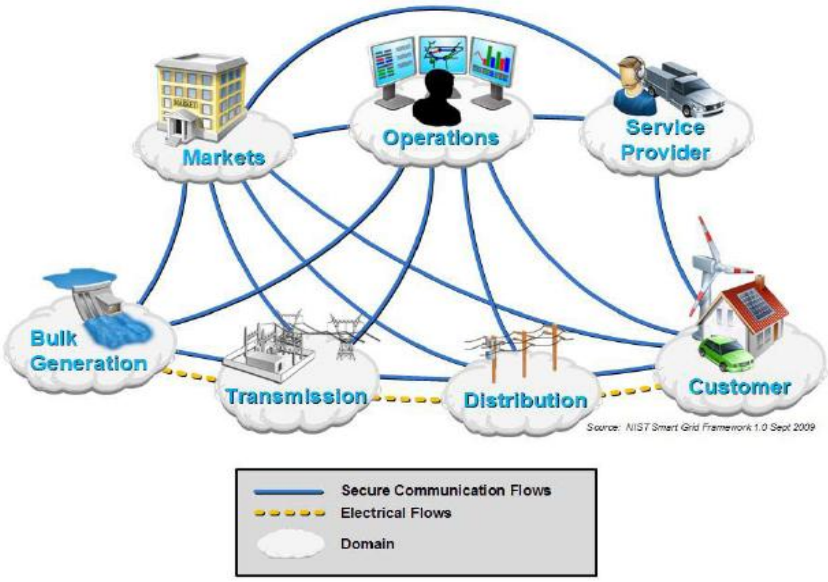

Figure 1. Conceptual model of the smart grid [17]

One of the algorithms used for optimization process is the swarm intelligence based firefly algorithm. In this study;In the second part of this article, the structure of improved firefly algorithm; In the third part, the power optimization problem in the smart grid, in the fourth part the application of the improved firefly algorithm to a sample test system and comparison of the results, in the fifth part consists of conclusion.

II. OPTIMIZATION CONCEPT IN SMART GRID AND SOME ALGORITHMS USED

Smart grid optimization; It can be summarized as the distribution of electricity produced in generators in the network and providing the most appropriate power exchange between the existing busbars in the network without exceeding the physical and operational limits of the elements used in the networks. Especially with the concept of smart grid; the integration of distributed energy sources into the grid makes the network more complex. The power flow of the grid must be optimal in order to ensure a continuous and inexpensive energy supply to the consumers in the electrical power system. Especially in smart grids, it is more preferable to use swarm intelligence and biological-based algorithms for optimization. Herd; It refers to a stack of distributed individuals that interact with each other. Individuals may be bees, ants, fireflies or human beings. *N* delegates in the herds work together to achieve a goal-oriented behavior. This easily observable collective intelligence emerges frequently from repetitive behaviors. Representatives use simple individual rules to manage their activities and achieve their herd objectives through interaction with the rest of the group. There is some sort of self-organization from the sum of the group activities [18]. One of the most preferred algorithms based on swarm intelligence is the firefly algorithm.

2.1 Firefly Algorithm

Fireflies are a species of beetles, known for their flashing lights as they fly at night in spring and summer. Fireflies are animals known for their green-yellow light produced by chemical reactions in their bodies. The firefly algorithm was developed by Xin-She Yong in 2008 based on the refraction behavior of fireflies [19]. The luminosity characteristic based on the algorithm is summarized with the following 3 rules:

a) There is no gender discrimination between fireflies. Therefore, fireflies may want to influence each other without looking at gender.
b) The degree of brightness determines the effectiveness factor in fireflies. The firefly, which has a lot of brightness, will attract the little firefly itself. If the fireflies have the same luminosity, they will act instinctively.
c) The brightness of the firefly will be chosen according to the problem function and the type of problem.

2.1.1 Initiation of population

In the first stage of the problem, all the fireflies in the environment are positioned instinctively in the search space *S* or a problem type for a problem with the size *d*. *m* firefly optimization in the environment is determined the solution of the problem by looking at the suitability value of *xi*.

$$f(x^*) = \min_{x \in S} f(x) \tag{1}$$

Since the optimization process is also a minimization process, the main goal in the system solution is to obtain the solution that f(x) minimizes the objective function x^*. The previously determined objective function is the solution of fireflies, and as a result of this, Ploss also shows the brightness of the fireflies [20].

2.1.2 Determination of Interaction Rate

Each firefly in the solution space has a different β value, which determines the rate at which it affects other fireflies. To determine whether the *i-th* firefly is affected by the *j-th* firefly insect, firstly the degree of gloss of the *i-th* firefly is examined. The determined degree of brightness should be lower than the *j-th* firefly and the cost values of the solutions obtained are compared. If the *xi* solution is in a position to be affected by the *xj* solution, it is determined that the *i-th* firefly is less brighter than the *j-th* firefly, and the decreasing exponential function should be selected by the effect of the distance of *i* to *j* to determine the β value [21].

$$r_{i,j} = \left\| x_i - x_j \right\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{2}$$

$$\beta = \beta_0 . e^{-\gamma . r_{i,j}} \tag{3}$$

In the case of the β_0 parameter in equation (3), the activity parameter and the parameter are the light absorption coefficient. In general, β_0 is a number selected in the range [0 1]. If $\gamma = 0$ is selected, a constant activity value and $\gamma = \infty$ is selected from equation (3), if the event is selected to be very close to zero. If the search space is included in the optimized characteristic length γ parameter; calculated γ as follows:

$$\gamma = \frac{\gamma_0}{r_{maks}} \tag{4}$$

$$r_{maks} = maksd(x_i, x_j), \forall x_i, x_j \in S \tag{5}$$

The γ_0 parameter in equation (4) is a fixed number selected in the range [0 1].

2.1.3 Detemination the position

In the case of a firefly *j* is affected by firefly *i* that has *k* dimension, its position in the solution space is determined according to equation (6) [22].

$$x_{i,k} = (1-\beta).x_{i,k} + \beta.x_{j,k} + u_{i,k} \tag{6}$$

In Equation (7), $u_{i,k}$ randomly determines the location of the *i-th* firefly and it is expressed as follows, depending on the random1 value in the range of [0 1] and the parameter α set in the range [0 1]:

$$u_{i,k} = \alpha.(random1 - \frac{1}{2}) \tag{7}$$

The firefly with the best cost value will move according to equation (8) in the search space.

$$x_i maks_{,k} = x_i maks_{,k} + u_i maks_{,k} \; k=1,2,..,d \tag{8}$$

$$u_i maks_{,k} = \alpha.(rand\,1 - \frac{1}{2}) \tag{9}$$

The flowchart of the firefly algorithm is shown in Figure 2.

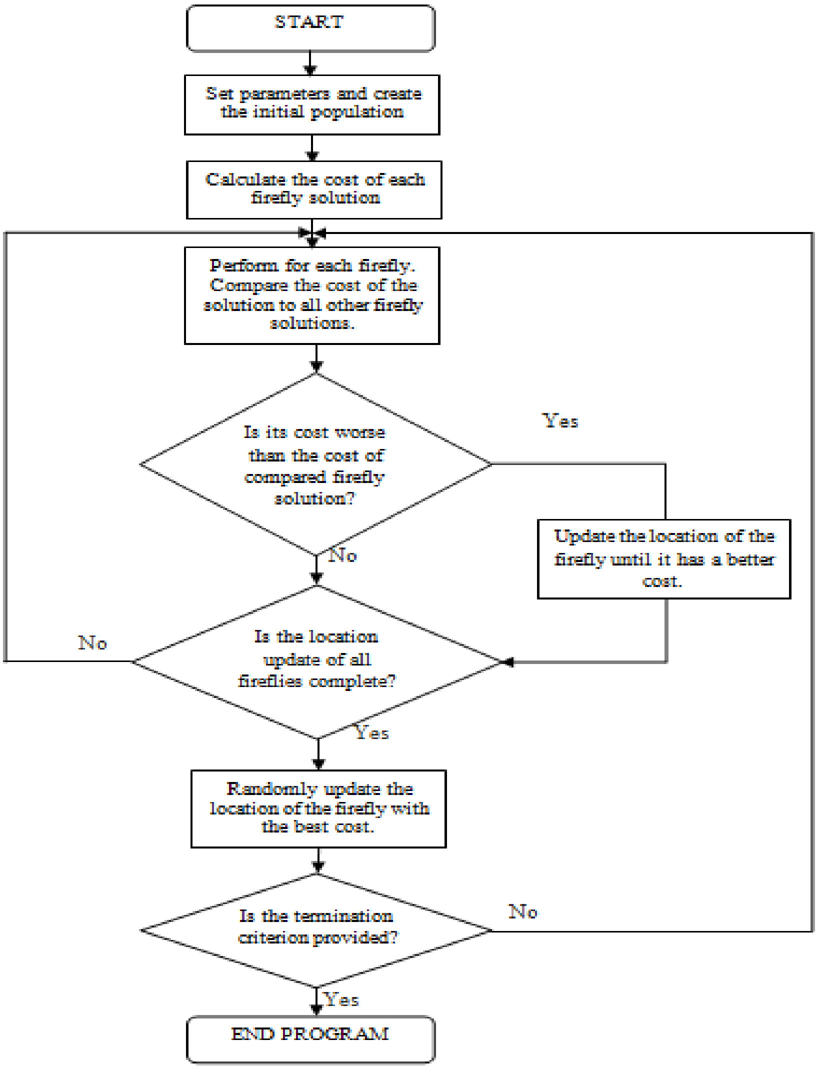

Figure 2. Flowchart of firefly algorithm

2.2 Calculation of optimal power loss by using firefly algorithm

The steps to calculate the optimum power loss with the help of the firefly algorithm are as follows:
Step 1: Enter the input data of the system to be solved.
Step 2: Get the initial population of the firefly. *Xi (i = 1,2,…,n)*
Step 3: Determine the power loss function (P_{loss}).
Step 4: Determine the light intensity of I_i in x_i with the function *f(xi).*
Step 5: Specify the absorption coefficient (γ).
Step 6: Identify the firefly with the best cost.
Step 7: Stop the algorithm when the optimum result is reached or the number of iterations previously determined is reached; otherwise, continue to run the program by increasing the number of iterations.

III. MATHEMATICAL MODEL OF OPTIMUM POWER LOSS PROBLEM

This kind of problem is a minimization problem and is formulated as equation (10):

$$\begin{aligned} g(x,u) &= 0 \\ h(x,u) &\le 0 \end{aligned} \tag{10}$$

The objective is to minimize power losses (active and reactive). P_{loss} is given in equation (11).

$$P_{loss} = \sum_{i=1, j\neq i}^{Nb} G_{ij}(V_i^2 + V_j^2 - 2V_iV_j \cos(\theta_{ij})) \tag{11}$$

P_{loss}: Total actual power loss (MW)
Nb: Number of busbar
V_i ve V_j: voltage at the end of the *i-th* and *j-th* busbar
G_{ij}: Conductivity of transmission line between *i* and *j* busbar
θ_{ij}: Phase angle between *i* and *j* busbar

3.1 Equality Limitations

To achieve equation (11), it is necessary to equalize the magnitude and angle of the voltage in each busbar as in equation (12).

$$\begin{aligned} &\sum_{j=1}^{N} |V_i||V_j|(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) - P_{Gi} + P_{Di} = 0 \\ &\sum_{j=1}^{N} |V_i||V_j|(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) - Q_{Gi} + Q_{Di} = 0 \end{aligned} \tag{12}$$

Vi,Vj : Voltage at the end of the *i-th* and *j-th* busbar
G_{ij}: Conductivity of transmission line between *i* and *j* busbar
P_{Gi}: Active output power of the *i-th* generator
Q_{Gi}: Reactive output power of *i-th* generator
P_{Di}: Active output load of the *i-th* busbar
Q_{Di}: Reactive output load of the *i-th* busbar
θ_{ij}: θ_i-θ_j (phase angle between *i* and *j* busbar)

The generator voltages must be within the permissible limits.

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max} \tag{13}$$

The active and reactive power generated by the algoritm must be within the permissible limits.

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \tag{14}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \tag{15}$$

IV. TEST BUSBAR SYSTEM AND APPLICATION OF ALGORITHM TO TEST SYSTEM

The IEEE30 busbar test system will be used to implement the firefly algorithm in the program written in Matlab GUI environment. The IEEE30 busbar test system consists of 41 lines, 6 generators and 4 step transformers available in lines 6-9, 6-10, 4-12, 28-27 as shown in Figure 3. The initial values of the IEEE-30 busbar system are given in Table 2.

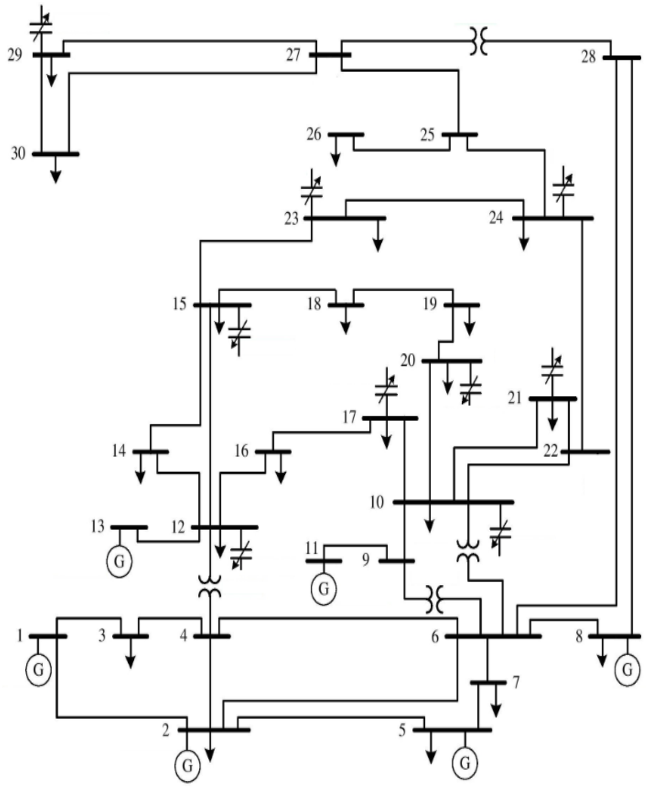

Figure 3. IEEE30-busbar test system [23]

Table 2. Introduction of IEEE30-busbar system

Busbar total numbers		30		
Line total numbers		41		
Generator total numbers		6		
Tap changing transformer total numbers		4		
Shont capacitor total numbers		9		
Load buse total numbers		24		
Active power loss's initial value		5.811 MW		
Reactive power loss's initial value		32.41 MVar		
Various variables' limits				
	Voltage of generators (p.u)	**Transfomer tap ratio**	**Capacitor banks (MVar)**	**Load Voltage (p.u)**
Min	0.95	0.9	0	0.95
Max	1.1	1.1	5	1.05

The base value of the voltage is S_{base} = 100MVA, the base value of the voltage is V_{base} = 100 kV and the tolerance rate is 10%.

Table 3. Optimization results of the IEEE 30-busbar test system (busbar voltages)

BusbarNo	Initial Values	Values obtained as a result of improved firefly algorithm	Bus bar No	Initial Values	Values obtained as a result of improved firefly algorithm
1	1.0228	1.0558	16	1.0599	1.0184
2	1.0622	1.0451	17	1.0585	1.0103
3	1.0411	1.0451	18	1.0450	1.0047
4	1.0449	1.0418	19	1.0440	1.0002
5	1.0953	1.0253	20	1.0488	1.0034
6	1.0503	1.0304	21	1.0515	1.0049
7	1.0605	1.0206	22	1.0513	1.0058
8	1.0646	1.0240	23	1.0404	1.0107
9	1.0917	1.0203	24	1.0305	1.0024
10	1.0651	1.0135	25	1.0056	1.0157
11	1.0850	1.0484	26	0.9877	0.9980
12	1.0686	1.0341	27	0.9990	1.0327
13	1.0850	1.0953	28	1.0504	1.0248
14	1.0557	1.0210	29	0.9826	1.0243
15	1.0520	1.0177	30	0.9692	1.0082

The initial voltage values of the IEEE-30 busbar test system and the optimum voltage values obtained by firefly algorithm are shown in Table 3. When the voltage values in Table 3 are examined, it is seen that the busbar voltages obtained are between the optimum voltage values (0.95 p.u $\leq V_{busbar} \leq$1.1 p.u). The comparison of the initial and the optimum voltage values are given in Figure 4. Referring to Figure 4, the busbar voltages appear to be between the optimum values (0.95 p.u $\leq V_{busbar}\leq$ 1.1 p.u). In Table 4, firefly algorithm results are compared by different number of nutrients, number of iterations and other parameter changes.

Table 4. Firefly algorithm P_{loss} values

Number of Nutrients	25	50	100	150	300
Number of Iterations	100	100	100	200	100
Alpha coefficient	0,5	0,5	0,6	0,65	0,55
P_{loss} (MW)	4,64	4,45	4,55	4,39	**4,42**

When Table 4 is examined, the best P_{loss} value obtained as a result of the program is calculated as 4,42 MW.

Table 5. Statistical Analysis of Algorithms(100 Trial Runs)

Algorithm	**Best value (MW)**	**Worst value (MW)**	**Mean value (MW)**	**Standard deviation**	**Simulation time (Sec.)**
DE [24]	NR*	NR*	NR*	NR*	NR*
GSA [25]	NR*	NR*	NR*	NR*	NR*
BBO [26]	4.5511	4.5522	4.5515	NR*	110
PSO [27]	4.6282	4.7986	4.7363	0.0011	130
OGSA[28]	4.4984	4.6833	4.6397	0.0007	138
Improved firefly algorithm	**4.4214**	4.5626	4.4746	0.00068	102

NR* means not reported

Table 5 shows the statistical analysis of the proposed and compared algorithms. All algorithms were run 100 times to compare the best, worst and mean values, standard deviation and simulation time. Since the algorithms are stochastic, the single operation does not make sense. Therefore, the algorithms were run 100 times during the comparison and the obtained results are given in Table 5. The values of the compared algorithms were obtained from the relevant reference. It is seen in Tablo 5 that improved firefly algorithm gives better results than other algorithms.

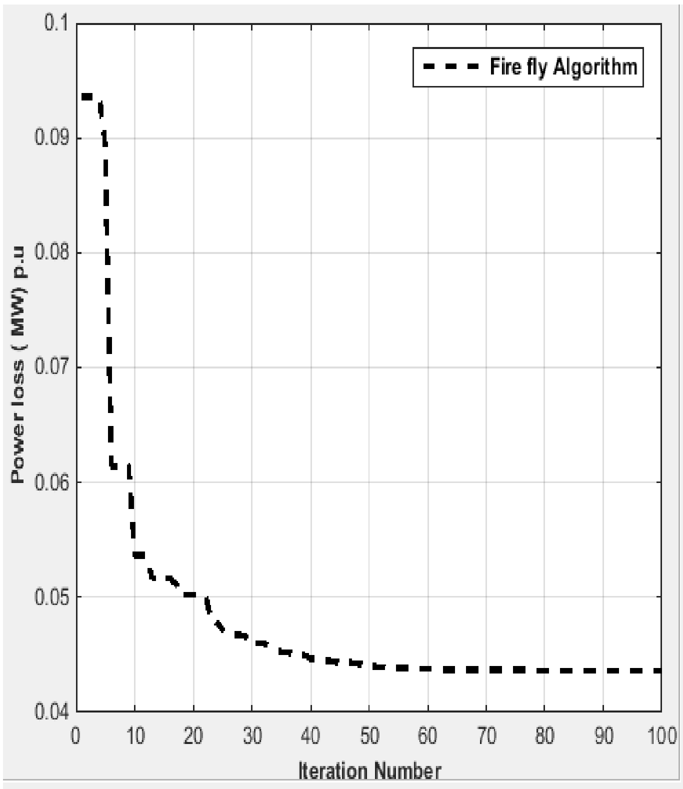

Figure 4. Graph of change of optimum power loss according to iteration number

Figure 4 shows the graph of the change in the optimum power loss according to the number of iterations. When the graph is obtained, the number of nutrient sources given in Table 4: 300 and the number of iterations 100 are entering program to obtain P_{loss} value that is plotted as p.u and its value is calculated as 0.04214. When Table 2 is analyzed, the power loss before the optimization process is 5.811 MW. The optimal values of the control variables were obtained from the program written in Matlab GUI and the values are given in Table 5. The proposed algorithm's results were compared with DE, GSA, BBO, PSO, CLPSO and OGSA algorithms. The results of the comparison algorithms were obtained from the relevant references. The best optimized P_{loss} value obtained in the improved firefly algorithm is **4.4214 MW**. Among the algorithms given in Table 5, the P_{loss} value of the OGSA algorithm with the best value is 4.4984 MW. The result of the proposed algorithm is 0.077 MW better than this value and smart grid optimization has been achieved with 1.711 % less power loss. The initial power loss of the IEEE-30 busbar test system was 5.81MW which decreased to 4.4214 MW as a result of the improved firefly algorithm. The power loss value decreased by 1.3886 MW and 23.9%.

V. CONCLUSION

Power loss in the smart grid affects system performance and reliability. One of the algorithms used to optimize power loss is the firefly algorithm. In this study, using the firefly algorithm in the Matlab GUI environment for the optimum power loss calculation in the smart grid, the program was applied to the IEEE30-busbar system and the results were compared with the other heuristic and herd algorithms. The firefly algorithm has calculated a more optimized value than other algorithms. The most important disadvantage is the number of parameters used is more. The values obtained by the firefly algorithm are within the permissible limits for the optimum power loss in the smart grid and will allow the system to run more stable. Standard deviation and simulation time are less than other comparative algorithms. Therefore, the algorithm can be proposed as a promising method to solve other optimization problems in the smart grid (optimum fuel cost, voltage profile improvement, etc.). In the following studies, the algorithm will be applied to different current bus test systems and robustness and superiority will be investigated for different optimization problems.

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