



Research article

Diminution of real power loss by novel Galápagos Penguin Algorithm

Lenin Kanagasabai *

Department of EEE, Prasad V.Potluri Siddhartha Institute of Technology, Kanuru, Vijayawada, Andhra Pradesh, 520007, India



ARTICLE INFO

Keywords:

Electrical engineering
Energy
Industrial engineering
Computer-Aided engineering
Optimal reactive power
Transmission loss
Galápagos Penguin

ABSTRACT

In this work Galápagos Penguin Algorithm (GPA) has been applied to solve optimal reactive power problem. Galápagos penguins' foraging activities are modeled to solve the problem. As a team Galápagos Penguin feed on food and by intra-group communication it communicates each other. Once a Galápagos penguin finds a superior food source then it will act as new-fangled local guide in which Foraging of the team is an autocatalytic procedure. To dive in-depth Galápagos Penguin takes up extra energy to find about the information of food. Until the oxygen get exhausted Galápagos Penguin execute the recurring dives, subsequently it will move around to another group in search of food. Galápagos penguin modernizes its group membership based on food availability degree of different groups. In standard IEEE 14, 30, 57, 118, 300 bus systems Proposed Galápagos Penguin Algorithm (GPA) is evaluated and simulation results show the GPA reduced the power loss efficiently.

1. Introduction

Reactive power problem plays a key role in secure and economic operations of power system. Optimal reactive power problem has been solved by variety of types of methods like Newton's method, interior point method, successive quadratic programming method [1, 2, 3, 4, 5, 6] has been utilized to solve the optimal reactive power problem. However many scientific difficulties are found while solving problem due to an assortment of constraints. Evolutionary techniques such as gravitational search, Ant Lion Optimizer, symbiotic organism search algorithm [7, 8, 9, 10, 11, 12, 13, 14, 15, 16] are applied to solve the reactive power problem, but the main problem is many algorithms get stuck in local optimal solution & failed to balance the Exploration & Exploitation during the search of global solution. In this work, Galápagos Penguin Algorithm (GPA) has been applied to solve optimal reactive power problem. Galápagos Penguin is a sea bird [17] and its wings are perfect for swimming; it stays under the water for up to 20 min. Normally Galápagos Penguin feed on krill, small fish, squid, and crustaceans. Galápagos Penguin are forced to come to the surface for air after every foraging journey and is restricted by the oxygen reserves also the speed at which they make use of it. Through intra-group communication Galápagos Penguin communicates each other and when one Galápagos penguin finds a superior food source then it act as new-fangled local guide in which Foraging of the team is an autocatalytic procedure. When there is food shortage in the group Galápagos penguin will transfer to unite another group. Galápagos Penguin modernizes its group

membership based on food availability degree of different groups. In the proposed algorithm both the exploration and exploitation has been balanced in order to obtain the optimal solution. Validity of the Proposed Galápagos Penguin Algorithm (GPA) has been tested in standard IEEE 14, 30, 57, 118, 300 bus systems and results show the projected GPA reduced the power loss effectively.

2. Problem formulation

Objective of the problem is to reduce the true power loss:

$$F = P_L = \sum_{k \in Nbr} g_k (V_i^2 + V_j^2 - 2V_i V_j \cos \theta_{ij}) \quad (1)$$

where F- objective function, P_L - Power loss.

Voltage deviation given as follows:

$$F = P_L + \omega_v \times \text{Voltage Deviation} \quad (2)$$

ω_v - Weight factor.

Voltage deviation given by:

$$\text{Voltage Deviation} = \sum_{i=1}^{Npq} |V_i - 1| \quad (3)$$

* Corresponding author.

E-mail address: gklenin@gmail.com.

<https://doi.org/10.1016/j.heliyon.2019.e03001>

Received 30 August 2019; Received in revised form 30 October 2019; Accepted 4 December 2019

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2.1. Constraint (equality)

$$P_G = P_D + P_L \quad (4)$$

where P_G and P_D indicates the power generation and power demand.

2.2. Constraints (inequality)

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \quad (5)$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \quad (6)$$

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \quad (7)$$

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \quad (8)$$

$$Q_c^{min} \leq Q_c \leq Q_c^{max}, i \in N_C \quad (9)$$

where reactive power compensators indicated by Q_c , dynamic tap setting of transformers –dynamic indicated by T , level of the voltage in the generation units given by V_g , slack generator indicated by P_{Gslack} , level of voltage on transmission lines symbolized by V_L , generation units reactive power indicated by Q_G , apparent power symbolized by S_L .

3. Galápagos Penguin Algorithm

Galápagos Penguin is a sea bird and its wings are perfect for swimming; it stays under the water for up to 20 min. Normally Galápagos Penguin feed on krill, small fish, squid, and crustaceans. To dive in-depth Galápagos Penguin takes up extra energy to find about the information of food.

Galápagos Penguin are forced to come to the surface for air after every foraging journey and is restricted by the oxygen reserves also the speed at which they make use of it. Galápagos penguins' foraging activities are modeled as rules as follows;

Rule 1: Galápagos Penguin consists of numerous groups. Depending on food accessibility in the analogous foraging area every group enclose Galápagos penguins.

Rule 2: Based on energy gain each group of Galápagos Penguin starts foraging in an exact depth under the water.

Rule 3: Naturally Galápagos Penguin feed as a team and go behind their local guide. Until the oxygen reserves are depleted they examine the water for food.

Rule 4: Galápagos Penguin comes back on surface to share the information about the locations and abundance of food sources with its local affiliates through intra-group communication.

Rule 5: Through inter-group communication Galápagos Penguin leaves the group to join another group when food availability becomes less.

3.1. Modernization of swimming track

At time $t+1$ Galápagos penguin j swims to a new-fangled location in “ Ω ” as defined by the following equation,

$$y_j^i(t+1) = y_j^i(t) + O_j^i(t) \times \text{random}() \times (y_{local\ best}^i - y_j^i(t)) \quad (10)$$

where $y_j^i(t)$ and $O_j^i(t)$ indicates the Galápagos Penguin movement and oxygen reserve.

Galápagos Penguin follow local leader and swimming is hasten by the oxygen reserve which replicate its fitness condition.

3.2. Modernization of Oxygen reserve

Oxygen reserve of the Galápagos penguin is modernized subsequent to each dive by,

$$O_{t+1}^i = O_t^i + \left(f(y_j^i(t+1)) - f(y_j^i(t)) \right) \times \|y_j^i(t+1) - y_j^i(t)\| \quad (11)$$

Modernization of Oxygen reserve is done with reference to objective function. When new-fangled solution is superior to the preceding one then the oxygen reserve augments. Galápagos Penguin executes recurring dives until the oxygen is exhausted, subsequently Galápagos penguin will move around to another group.

3.3. Communication between intra-group

When one Galápagos penguin finds a superior food source then it act as new-fangled local guide in which Foraging of the team is an autocatalytic procedure.

3.4. Modernization of food plenty available status

Food available status is linked to a group which indicate the energy content of prey captured by the group and it estimated by the capacity of Eaten Fish (CEF), which is computed by,

$$CEF^i(t+1) = CEF^i(t) + \sum_{j=1}^{d_i} (O_{t+1}^j - O_t^j) \quad (12)$$

3.5. Modernization of group membership

When there is food shortage in the group Galápagos penguin will transfer to unite another group. Galápagos Penguin modernizes its group membership $Q_i(t+1)$ based on food availability degree of different groups.

$$Q_i(t+1) = \frac{CEF^i(t)}{\sum_{j=1}^k CEF^j(t)} \quad (13)$$

a	Solution space generated
b	Within bounded region Galápagos penguin are generated for each groups
c	while end condition is not reached do
d	for each Galápagos penguin oxygen reserve is initialized
e	For every group “i” do
f	For every Galápagos penguin “j” in this group do
g	Position of the Galápagos penguin enhanced as follows;
	Input; solution space, maximum distance
	Output; K region centers in the space (solution)
	Center of the primary group arbitrarily chosen and indicated by C_0
	$i \leftarrow 1$
	While $i < K$ do
	Center C_i arbitrarily chosen for the subsequent group
	$j \leftarrow 0$
	While $j < id$ do
	When $distance(C_i, C_j) > \text{maximum distance}$ then
	$j \leftarrow j + 1$
	Otherwise chose Center C_i again
	End if
	End while
	$i \leftarrow i + 1$

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End while
End
h Solution enhancement stratagem done by
Input; $y_j^i, O_j^i, y_{local\ best}^i$
Output; new $y_j^i, y_{local\ best}^i$
While $O_j^i > 0$ do
y_j^i Dive done through; $y_j^i(t+1) = y_j^i(t) + O_j^i(t) \times random() \times (y_{local\ best}^i - y_j^i(t))$
When y_j^i enhances then,
Modernize y_j^i
Modernize $y_{local\ best}^i$ when y_j^i pound $y_{local\ best}^i$
End if
Modernize O_j^i by; $O_{t+1}^i = O_t^i + (f(y_j^i(t+1)) - f(y_j^i(t))) \times y_j^i(t+1) - y_j^i(t)$
End while
End
i Modernization of Food plenty available status by
$CEF^i(t+1) = CEF^i(t) + \sum_{j=1}^d (O_{t+1}^i - O_t^i)$
j End
k Modernize the global most excellent solution
l Modernization of Group membership done by,
$Q_i(t+1) = \frac{CEF^i(t)}{\sum_{j=1}^k CEF^j(t)}$
m Reallocate Galápagos Penguin to groups with reference to membership function;
n Discard the group when no members found;
o End while
p End

4. Simulation results

In standard IEEE 14 bus system the validity of the projected Galápagos Penguin Algorithm (GPA) has been tested, Table 1 shows the constraints of control variables Table 2 shows the limits of reactive power generators and comparison results with particle swarm optimization (PSO), modified particle swarm optimization (MPSO), self-adaptive real coded Genetic algorithm (SARGA), Evolutionary Programming (EP) are presented in Table 3.

Then the projected Galápagos Penguin Algorithm (GPA) has been tested, in IEEE 30 Bus system. Table 4 shows the constraints of control variables, Table 5 shows the limits of reactive power generators and comparison results with particle swarm optimization (PSO), modified particle swarm optimization (MPSO), self-adaptive real coded Genetic algorithm (SARGA), Evolutionary Programming (EP) are presented in Table 6.

Table 1. Constraints of control variables.

System	Variables	Minimum (PU)	Maximum (PU)
IEEE 14 Bus	Generator Voltage	0.95	1.1
	Transformer Tap	0.9	1.1
	VAR Source	0	0.20

Table 2. Constrains of reactive power generators.

System	Variables	Q Minimum (PU)	Q Maximum (PU)
IEEE 14 Bus	1	0	10
	2	-40	50
	3	0	40
	6	-6	24
	8	-6	24

Table 3. Simulation results of IEEE –14 system.

Control variables	Base case	MPSO [19]	PSO [19]	EP [19]	SARGA [19]	GPA
VG–1	1.060	1.100	1.100	NR*	NR*	1.010
VG–2	1.045	1.085	1.086	1.029	1.060	1.012
VG–3	1.010	1.055	1.056	1.016	1.036	1.017
VG–6	1.070	1.069	1.067	1.097	1.099	1.020
VG–8	1.090	1.074	1.060	1.053	1.078	1.002
Tap 8	0.978	1.018	1.019	1.04	0.95	0.900
Tap 9	0.969	0.975	0.988	0.94	0.95	0.901
Tap 10	0.932	1.024	1.008	1.03	0.96	0.924
QC–9	0.19	14.64	0.185	0.18	0.06	0.146
PG	272.39	271.32	271.32	NR*	NR*	271.64
QC (Mvar)	82.44	75.79	76.79	NR*	NR*	74.79
Reduction in PLoss (%)	0	9.2	9.1	1.5	2.5	24.14
Total PLoss (Mw)	13.550	12.293	12.315	13.346	13.216	10.279

NR* - Not reported.

Then the proposed Galápagos Penguin Algorithm (GPA) has been tested, in IEEE 57 Bus system. Table 7 shows the constraints of control variables, Table 8 shows the limits of reactive power generators and comparison results with particle swarm optimization (PSO), modified

Table 4. Constraints of control variables.

System	Variables	Minimum (PU)	Maximum (PU)
IEEE 30 Bus	Generator Voltage	0.95	1.1
	Transformer Tap	0.9	1.1
	VAR Source	0	0.20

Table 5. Constrains of reactive power generators.

System	Variables	Q Minimum (PU)	Q Maximum (PU)
IEEE 30 Bus	1	0	10
	2	-40	50
	5	-40	40
	8	-10	40
	11	-6	24
	13	-6	24

Table 6. Simulation results of IEEE –30 system.

Control variables	Base case	MPSO [19]	PSO [19]	EP [19]	SARGA [19]	GPA
VG–1	1.060	1.101	1.100	NR*	NR*	1.010
VG–2	1.045	1.086	1.072	1.097	1.094	1.012
VG–5	1.010	1.047	1.038	1.049	1.053	1.063
VG–8	1.010	1.057	1.048	1.033	1.059	1.001
VG–12	1.082	1.048	1.058	1.092	1.099	1.020
VG-13	1.071	1.068	1.080	1.091	1.099	1.041
Tap11	0.978	0.983	0.987	1.01	0.99	0.902
Tap12	0.969	1.023	1.015	1.03	1.03	0.910
Tap15	0.932	1.020	1.020	1.07	0.98	0.900
Tap36	0.968	0.988	1.012	0.99	0.96	0.901
QC10	0.19	0.077	0.077	0.19	0.19	0.063
QC24	0.043	0.119	0.128	0.04	0.04	0.109
PG (MW)	300.9	299.54	299.54	NR*	NR*	298.67
QC (Mvar)	133.9	130.83	130.94	NR*	NR*	130.73
Reduction in PLoss (%)	0	8.4	7.4	6.6	8.3	18.18
Total PLoss (Mw)	17.55	16.07	16.25	16.38	16.09	14.358

NR* - Not reported.

Table 7. Constraints of control variables.

System	Variables	Minimum (PU)	Maximum (PU)
IEEE 57 Bus	Generator Voltage	0.95	1.1
	Transformer Tap	0.9	1.1
	VAR Source	0	0.20

Table 8. Constrains of reactive power generators.

System	Variables	Q Minimum (PU)	Q Maximum (PU)
IEEE 57 Bus	1	-140	200
	2	-17	50
	3	-10	60
	6	-8	25
	8	-140	200
	9	-3	9
	12	-150	155

Table 9. Simulation results of IEEE –57 system.

Control variables	Base case	MPSO [19]	PSO [19]	CGA [19]	AGA [19]	GPA
VG 1	1.040	1.093	1.083	0.968	1.027	1.020
VG 2	1.010	1.086	1.071	1.049	1.011	1.012
VG 3	0.985	1.056	1.055	1.056	1.033	1.031
VG 6	0.980	1.038	1.036	0.987	1.001	1.010
VG 8	1.005	1.066	1.059	1.022	1.051	1.033
VG 9	0.980	1.054	1.048	0.991	1.051	1.010
VG 12	1.015	1.054	1.046	1.004	1.057	1.043
Tap 19	0.970	0.975	0.987	0.920	1.030	0.954
Tap 20	0.978	0.982	0.983	0.920	1.020	0.932
Tap 31	1.043	0.975	0.981	0.970	1.060	0.921
Tap 35	1.000	1.025	1.003	NR*	NR*	1.014
Tap 36	1.000	1.002	0.985	NR*	NR*	1.002
Tap 37	1.043	1.007	1.009	0.900	0.990	1.003
Tap 41	0.967	0.994	1.007	0.910	1.100	0.991
Tap 46	0.975	1.013	1.018	1.100	0.980	1.012
Tap 54	0.955	0.988	0.986	0.940	1.010	0.970
Tap 58	0.955	0.979	0.992	0.950	1.080	0.961
Tap 59	0.900	0.983	0.990	1.030	0.940	0.960
Tap 65	0.930	1.015	0.997	1.090	0.950	1.002
Tap 66	0.895	0.975	0.984	0.900	1.050	0.951
Tap 71	0.958	1.020	0.990	0.900	0.950	1.000
Tap 73	0.958	1.001	0.988	1.000	1.010	1.002
Tap 76	0.980	0.979	0.980	0.960	0.940	0.960
Tap 80	0.940	1.002	1.017	1.000	1.000	1.001
QC 18	0.1	0.179	0.131	0.084	0.016	0.173
QC 25	0.059	0.176	0.144	0.008	0.015	0.161
QC 53	0.063	0.141	0.162	0.053	0.038	0.141
PG (MW)	1278.6	1274.4	1274.8	1276	1275	1270.10
QC (Mvar)	321.08	272.27	276.58	309.1	304.4	272.32
Reduction in PLoss (%)	0	15.4	14.1	9.2	11.6	23.69
Total PLoss (Mw)	27.8	23.51	23.86	25.24	24.56	21.213

NR* - Not reported.

Table 10. Constraints of control variables.

System	Variables	Minimum (PU)	Maximum (PU)
IEEE 118 Bus	Generator Voltage	0.95	1.1
	Transformer Tap	0.9	1.1
	VAR Source	0	0.20

Table 11. Simulation results of IEEE –118 system.

Control variables	Base case	MPSO [19]	PSO [19]	PSO [19]	CLPSO [19]	GPA
VG 1	0.955	1.021	1.019	1.085	1.033	1.012
VG 4	0.998	1.044	1.038	1.042	1.055	1.040
VG 6	0.990	1.044	1.044	1.080	0.975	1.021
VG 8	1.015	1.063	1.039	0.968	0.966	1.002
VG 10	1.050	1.084	1.040	1.075	0.981	1.014
VG 12	0.990	1.032	1.029	1.022	1.009	1.020
VG 15	0.970	1.024	1.020	1.078	0.978	1.031
VG 18	0.973	1.042	1.016	1.049	1.079	1.044
VG 19	0.962	1.031	1.015	1.077	1.080	1.033
VG 24	0.992	1.058	1.033	1.082	1.028	1.017
VG 25	1.050	1.064	1.059	0.956	1.030	1.033
VG 26	1.015	1.033	1.049	1.080	0.987	1.052
VG 27	0.968	1.020	1.021	1.087	1.015	0.901
VG 31	0.967	1.023	1.012	0.960	0.961	0.900
VG 32	0.963	1.023	1.018	1.100	0.985	0.912
VG 34	0.984	1.034	1.023	0.961	1.015	1.000
VG 36	0.980	1.035	1.014	1.036	1.084	1.003
VG 40	0.970	1.016	1.015	1.091	0.983	0.964
VG 42	0.985	1.019	1.015	0.970	1.051	1.002
VG 46	1.005	1.010	1.017	1.039	0.975	1.000
VG 49	1.025	1.045	1.030	1.083	0.983	1.001
VG 54	0.955	1.029	1.020	0.976	0.963	0.922
VG 55	0.952	1.031	1.017	1.010	0.971	0.963
VG 56	0.954	1.029	1.018	0.953	1.025	0.954
VG 59	0.985	1.052	1.042	0.967	1.000	0.960
VG 61	0.995	1.042	1.029	1.093	1.077	0.972
VG 62	0.998	1.029	1.029	1.097	1.048	0.981
VG 65	1.005	1.054	1.042	1.089	0.968	1.004
VG 66	1.050	1.056	1.054	1.086	0.964	1.003
VG 69	1.035	1.072	1.058	0.966	0.957	1.052
VG 70	0.984	1.040	1.031	1.078	0.976	1.030
VG 72	0.980	1.039	1.039	0.950	1.024	1.021
VG 73	0.991	1.028	1.015	0.972	0.965	1.010
VG 74	0.958	1.032	1.029	0.971	1.073	1.013
VG 76	0.943	1.005	1.021	0.960	1.030	1.004
VG 77	1.006	1.038	1.026	1.078	1.027	1.002
VG 80	1.040	1.049	1.038	1.078	0.985	1.001
VG 85	0.985	1.024	1.024	0.956	0.983	1.010
VG 87	1.015	1.019	1.022	0.964	1.088	1.012
VG 89	1.000	1.074	1.061	0.974	0.989	1.041
VG 90	1.005	1.045	1.032	1.024	0.990	1.032
VG 91	0.980	1.052	1.033	0.961	1.028	1.001
VG 92	0.990	1.058	1.038	0.956	0.976	1.033
VG 99	1.010	1.023	1.037	0.954	1.088	1.002
VG 100	1.017	1.049	1.037	0.958	0.961	1.000
VG 103	1.010	1.045	1.031	1.016	0.961	1.011
VG 104	0.971	1.035	1.031	1.099	1.012	1.002
VG 105	0.965	1.043	1.029	0.969	1.068	1.051
VG 107	0.952	1.023	1.008	0.965	0.976	1.010
VG 110	0.973	1.032	1.028	1.087	1.041	1.013
VG 111	0.980	1.035	1.039	1.037	0.979	1.004
VG 112	0.975	1.018	1.019	1.092	0.976	1.092
VG 113	0.993	1.043	1.027	1.075	0.972	1.001
VG 116	1.005	1.011	1.031	0.959	1.033	1.003
Tap 8	0.985	0.999	0.994	1.011	1.004	0.944
Tap 32	0.960	1.017	1.013	1.090	1.060	1.002
Tap 36	0.960	0.994	0.997	1.003	1.000	0.953
Tap 51	0.935	0.998	1.000	1.000	1.000	0.934

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Table 11 (continued)

Control variables	Base case	MPSO [19]	PSO [19]	PSO [19]	CLPSO [19]	GPA
Tap 93	0.960	1.000	0.997	1.008	0.992	1.000
Tap 95	0.985	0.995	1.020	1.032	1.007	0.971
Tap 102	0.935	1.024	1.004	0.944	1.061	1.000
Tap 107	0.935	0.989	1.008	0.906	0.930	0.943
Tap 127	0.935	1.010	1.009	0.967	0.957	1.002
QC 34	0.140	0.049	0.048	0.093	0.117	0.003
QC 44	0.100	0.026	0.026	0.093	0.098	0.022
QC 45	0.100	0.196	0.197	0.086	0.094	0.160
QC 46	0.100	0.117	0.118	0.089	0.026	0.122
QC 48	0.150	0.056	0.056	0.118	0.028	0.041
QC 74	0.120	0.120	0.120	0.046	0.005	0.112
QC 79	0.200	0.139	0.140	0.105	0.148	0.101
QC 82	0.200	0.180	0.180	0.164	0.194	0.152
QC 83	0.100	0.166	0.166	0.096	0.069	0.124
QC 105	0.200	0.189	0.190	0.089	0.090	0.152
QC 107	0.060	0.128	0.129	0.050	0.049	0.130
QC 110	0.060	0.014	0.014	0.055	0.022	0.002
PG(MW)	4374.8	4359.3	4361.4	NR*	NR*	4362.14
QG(MVAR)	795.6	604.3	653.5	* NR*	NR*	610.10
Reduction in PLOSS(%)	0	11.7	10.1	0.6	1.3	13.89
Total PLOSS (Mw)	132.8	117.19	119.34	131.99	130.96	114.347

NR* - Not reported.

Table 12. Comparison of real power loss.

Parameter	Method EGA [21]	Method EEA [21]	Method CSA [20]	GPA
PLOSS (MW)	646.2998	650.6027	635.8942	610.1509

particle swarm optimization (MPSO), canonical Genetic algorithm (CGA), Adaptive Genetic (AGA) are presented in Table 9.

Then the Galápagos Penguin Algorithm (GPA) has been tested, in IEEE 118 Bus system. Table 10 shows the constraints of control variables and comparison results with particle swarm optimization (PSO), modified particle swarm optimization (MPSO), conventional particle swarm optimization (CLPSO) are presented in Table 11.

Then IEEE 300 bus system [18] is used as test system to authenticate the good performance of the Galápagos Penguin Algorithm (GPA). Table 12 shows the comparison of real power loss with Cuckoo Search Algorithm (CSA), Efficient Evolutionary Algorithm (EEA), and Enhanced Genetic Algorithms (EGA).

5. Conclusion

In this work Galápagos Penguin Algorithm (GPA) successfully solved the optimal reactive power problem. Through intra-group communication Galápagos Penguin communicates each other and when one Galápagos penguin finds a superior food source then it act as new-fangled local guide in which Foraging of the team is an autocatalytic procedure. When there is food shortage in the group Galápagos penguin will transfer to unite another group. Deeds Galápagos Penguin is modeled to solve the problem effectively. In standard IEEE 14, 30, 57, 118, 300 bus systems Galápagos Penguin Algorithm (GPA) have been tested and power loss has been reduced efficiently. Percentage of the power loss reduction has been improved. In future this work can be expanded to application of the proposed GPA algorithm to multi-objective reactive power optimization problem. Also to practical systems the projected algorithm can be applied in real time systems.

Declarations

Author contribution statement

Kanagasabai Lenin: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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