# Analysis of Optimal Power Flow Using Combined PSO-GSA Technique

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**Abstract:** Using a hybrid approach that incorporates both particle swarm optimization (PSO) and gravitational search algorithms (GSA), this project aims to find the best way for power systems to distribute their energy. A novel heuristic search optimization technique, the GSA is works on the law of gravity. While this strategy has many advantages, it suffers from sluggish search performance and memory constraints. In order to discover a solution to this problem, the PSO technique was utilized. PSO and GSA, were utilized in this investigation to discover the optimal power flow utilizing a combination of these two methodologies. The suggested optimization method merges the social thinking and local search features of particle swarm optimization with those of the GSA, therefore taking benefit of both algorithms. This study examines and evaluates an optimization technique for the optimal power flow problem, focusing on reducing fuel costs, improving the voltage profile, and minimizing real power losses. The investigation and assessment are conducted on the commonly used IEEE 30-bus test systems. The simulation findings showcase the robust and effective resolution of the optimum power transfer problem through the amalgamation of Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA).

**Keywords:** OPF and problem formulation, Particle swarm optimization (PSO) technique, Gravitational Search Algorithm (GSA) method, Combination of PSO-GSA, Simulation results.

## I. INTRODUCTION

The optimal power flow challenge is a crucial element in the planning process for achieving inexpensive scheduling, ensuring security, and managing power systems. The approach to the Optimal Power Flow (OPF) challenge seeks to satisfy numerous system operations while simultaneously maximizing a chosen objective function. This is accomplished by modifying the power system control variables in the most effective manner possible. [1]. The OPF problem was solved by applying both population-based and classical optimization strategies. [2,3]. Traditional optimization is predicated on identifying the global optimum. But these methods were limited to producing the local optimum because of problems with differentiability, non-linearity, and non-convexity. Through the utilization of population-based methodologies, OPF problems that involve a wide variety of objective functions as well as challenging limited optimization problems have been resolved. In recent times, a number of hybrid algorithms have been suggested as potential solutions to the OPF problem. A hybrid algorithm can be developed by integrating the advantages of each population-based method. In this paper, a hybrid PSO and GSA method called PSOGSA is proposed to address the OPF problem. In this paper, investigate the effectiveness of the suggested approach on a conventional IEEE 30-bus test system by employing multiple fitness function.

## II PROBLEM FORMULATION USING OPF

Increased efficacy of the power system for a specific purpose is the aim of optimal power flow (OPF), as their name suggests. This function, referred to as the goal function, is often minimized by the OPF program. Optimized power flow has the advantage of lowering system running costs. From this, any power system utility will gain a great deal. Any system's ideal generator, bus voltage, and transformer tap settings are defined using the OPF problem to save overall manufacturing costs. [4]. Optimization is the process of changing a device's or its attributes' inputs or outputs to obtain the lowest or largest output or outcome. It can also be done by mathematical procedures or experiments. System variables serve as the input to the process, which is controlled and produces the cost or fitness by the cost, goal, or fitness functions.
**Formulation of OPF issues**: It is feasible to follow up on OPF mathematical formulation concerns. [1]:

$$\text{Optimize} \quad g(a, b) \tag{1}$$
$$\text{Subject to} \quad f(a, b) = 0 \tag{2}$$

$$H(a, b) \leq 0 \quad (3)$$
$$a \in A \quad (4)$$

"g" = desired objective function, "a" = control variable's vector which having the output active power of generator ($P_G$), voltages of generator ($V_G$), tap settings of transformer (t), and the shunt compensations ($q_c$). "b" = Line loading $S_l$, reactive power of generator $Q_g$, load bus voltages $V_l$, and power of slack bus $P_{gSl}$ are dependent variables vector.

The equality constraints shown in Eq. (2) as common nonlinear equations function as,

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j \,(G_{ij} \cos \Theta_{ij} + B_{ij} \sin \Theta_{ij}) \quad (5)$$
$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j \,(G_{ij} \sin \Theta_{ij} + B_{ij} \cos \Theta_{ij}) \quad (6)$$

Where, i=1 to $N_B$ ($N_B$ is the number of busses)

Inequalities in equation (3) are imposed by constraints on the amount of the load bus voltage, the output of the generator reactive power, and the power transfer in the lines. These constraints are imposed by the equation.

$$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}, \quad i = 1 \text{ to } N_L \quad (7)$$
$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, \quad i = 1 \text{ to } N_G \quad (8)$$
$$S_{li} \leq S_{li}^{max}, \quad i = 1 \text{ to } N_{TL} \quad (9)$$

The area where the control variables for the issue may be implemented is defined by the limitations in Eq. (4). Among these limits are the size of the voltage of generator bus, transformer tap settings, shunt VAR correction, and generator active power output.

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max}, \quad i = 1 \text{ to } N_G \quad (10)$$
$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}, \quad i = 1 \text{ to } N_G \quad (11)$$
$$T_{i}^{min} \leq T_{i} \leq T_{i}^{max}, \quad i = 1 \text{ to } N_T \quad (12)$$
$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}, \quad i = 1 \text{ to } N_C \quad (13)$$

## III PARTICLE SWARM OPTIMIZATION (PSO)

PSO finds the optimal response by using an essential amount of floating particles inside the exploration area, which was mostly created by two-dimensional modeling of flocking birds. In the meantime, they are all focused on finding the best solution along each particle's journey. Particles thus consider the best known solution as well as their own optimal solutions. Every particle makes an effort to change its location by making use of its exact location, speed, and distance from $P_{best}$ and distance to $G_{best}$ during the process. [5,6]. A brief overview and explanation of the PSO method's core elements is provided below [7].

**Particle:** Let n be the total number of control variables, a potential solution is shown as an n is dimensional vector. If "P" = optimized parameters then during the time period T, the i$^{th}$ particle $P_i(T)$ may be described as follows,

$$P_i(T) = [P_i^1(T), \ldots. P_i^k(T), \ldots., P_i^n(T)] \quad (14)$$

**Population:** a set of N particles at time period T, i.e., $pop(T) = [P_1(T), \ldots, P_N(T)]^T$.

**Swarm**: a clump of particles in motion that, contrary to appearances, have a tendency to congregate.

**Particle velocity:** The n- dimensions vector signifying the speed of the particle, the velocity of the i$^{th}$ number particle, denoted as $V_i(T)$, can be shown as follows at the specific time (T) being referred to.

$$V_i(T) = [v_i^1(T), \ldots, v_i^k(T), \ldots, v_i^n(T)] \quad (15)$$

$v_i^k(T)$ = i$^{th}$ particle's velocity component with regard to the k$^{th}$ dimension.

**Individual best:** A particle maintains a comparison between its present fitness value and its best fitness value for the full time period prior to the present as it moves throughout the searching space. The individual best second name is $P_{best}$, is the position that corresponds to the best value that has been attained thus far *(T)*.

$$P_{besti}(T) = [p_{besti}^{1}(T), \ldots, p_{besti}^{k}(T), \ldots, p_{besti}^{n}(T)] \tag{16}$$

**Global best:** The highest rank among all positions already obtained for each individual best is known as global best ($G_{best}$); hence it may be represented as,

$$G_{best}(T) = [g_{best}^{1}(T), \ldots, g_{best}^{k}(T), \ldots, g_{best}^{n}(T)] \tag{17}$$

**Stopping criteria:** The terms and conditions that will result in the search being terminated. In the event that the value of t is more than the maximum number that is permitted, the search will be terminated.

## IV GRAVITATIONAL SEARCH ALGORITHM (GSA)

Rashedi created a brand-new stochastic search technique called the GSA. [8]. The seeking agents of the GSA are a collective of entities that engage in mutual interaction through the application of Newtonian gravity and the principles governing motion. This method views agents as things, with each agent's performance determined by its mass. Gravity acts as an attraction between all of these items, causing each object to move in the direction of the object with the most mass. A objective function is used to determine the mass's gravitational and inertial masses, and the results match the solution to the problem. Through suitable adjustment of the gravitational mass and inertial mass, the process is completed. The GSA might be considered a solitary mass system. It seems like a small artificial planet with masses that obey gravitational and motion principles. GSA can be explained using the stages shown below. [9-12]

**(a) Initialization:** If it is assumed that a system of mass exists in N dimension of search space, the mass of the $k^{th}$ point is given as follows. The mass is positioned initially in a random position,

$$X_k = (x_k^{1}, \ldots, x_k^{d}, \ldots, x_k^{n}), k = 1, 2, \ldots, N \tag{18}$$

**(b) Assessment of the physical condition of all agents:** As a result of the following, the highest and lowest levels of fitness for each agent are determined:

$$\text{best}(t) = \min_{j\in(1,\ldots,N)} \text{fit}_j(t) \tag{19}$$

$$\text{worst}(t) = \max_{j\in(1,\ldots,N)} \text{fit}_j(t) \tag{20}$$

$\text{fit}_j(t)$= Fitness of the $j^{th}$ agent at the moment of time t, best(t) and worst(t)= both the lowest and highest level of agent fitness.

**(c) Gravitational constant should be calculated:** The gravitational constant (g(t)) at a given time can be calculated utilizing the subsequent formula:

$$g(t) = g_0 \exp(-\beta \frac{t}{N}) \tag{21}$$

$g_0$ = Given the starting value of the gravitational constant and the fact that it was chosen at random, $\beta$ = Constant, t = current epoch (time), Number of iterations (N) in total.

**(d) Update on Gravitational mass and Inertia mass:** Following is a revised estimate of the masses of gravity and inertia.:

$$Mg_k(t) = \frac{mg_k(t)}{\sum_{j=1}^{N} mg_j(t)} \tag{22}$$

$$mg_k(t) = \frac{\text{fit}_k(t) - \text{worst}(t)}{\text{best}(t) - \text{worst}(t)} \tag{23}$$

**(e) Force determination:** The determination of force $F_k^d(t)$ operating on the $k^{th}$ agent as,

$$F_k^d(t) = \sum_{j\in bestkj\neq 0} rand_j \, F_{kj}^d(t) \tag{24}$$

**(f) Determine the acceleration and speed:** Calculate the $k^{th}$ agent's acceleration $a_k^d(t)$ and speed $v_k^d(t+1)$ in the $d^{th}$ dimension using gravity and motion rules.

$$a_k^d(t) = \frac{F_k^d(t)}{Mg_k^d(t)} \tag{25}$$

$$v_k^d(t+1) = rand_k \times v_k^d(t) + a_k^d(t) \tag{26}$$

**(g) Updating of agent position:** It is updated as $[x_k^d(t+1)]$ for the $k^{th}$ agent's subsequent location in the $d^{th}$ dimension.

$$x_k^d(t+1) = x_k^d(t) + v_k^d(t+1) \tag{27}$$

**(h) Repetition:** Up until the iterations meet the condition, the steps in (b) through (g) are repeated. The value that corresponds to the agent's location on a particular dimension is returned by the algorithm at the conclusion of each iteration. The value in question is the end outcome of optimization problems as a whole.

## V. COMBINATION OF PSO-GSA

Combining PSO's social reasoning with GSA's local search capabilities is the core idea underlying PSO-GSA ($g_{best}$). [14,15]. The following is a suggested method for combining these algorithms:

$$v_k^d(t+1) = u_1 v_k^d(t) + Z_1 u_2 a_k^d(t) + Z_2 u_3 (g_{best}^d(t) - x_k^d(t)) \tag{28}$$
$$k = 1, 2, \cdots, A \text{ and } d = 1, 2, \cdots, n.$$

$v_k^d(t)$ = $k^{th}$ agent's velocity component
$Z_1$ and $Z_2$ = positive constants, $u_1$, $u_2$, and $u_3$ = uniformly spaced random numbers between 0 and 1,
$a_k^d(t)$ = at N iterations, the $k^{th}$ agent's acceleration component
$g_{best}^d(t)$ = the best solution in $d^{th}$ dimension
A = total number of agents
n = number of control variables of the selected problem.

Agent placements have been adjusted in each iteration as,

$$x_k^d(t+1) = x_k^d(t) + v_k^d(t+1) \tag{29}$$
$$k = 1, 2, \cdots, A \text{ and } d = 1, 2, \cdots, n.$$

**Strategies for employing PSO-GSA to solve OPF as follow,**

- Determine and initialize PSO-GSA variables such A, $t_{max}$, $g_0$, β, $Z_1$, and $Z_2$.
- Generate a random sample of A agents. Between the two extremes of the control variables' ranges, we pick a random beginning point for each agent.
- Launch the power flow software.
- Determine the fitness value of each individual agent. Several different fitness functions are taken into consideration along the course of this text.
- Take into account the overall force that is operating in the different directions.
- Work out the acceleration of every agent.
- Determine each agent's velocity.
- Update position of each agent's.
- Continue with Steps 3 through 9 until the stop condition.
- Return best solution; stop.

## VI RESULTS AND DISCUSSION (on IEEE 30-bus System)

An experimental evaluation of the hybrid PSOGSA method implemented on a standard IEEE 30-bus system. Four transformers with tap settings limited in the range of 0.9 pu (lower) and 1.1 pu (higher) are located at lines 6-9, 6-10, 4-12, and 28-27. Six generators are positioned at busses 1, 2, 5, 8, 11, and 13 of the system. The numbers 11, 12, 15, 17, 20, 21, 23, 24, and 29 make up the shunt VAR compensation buses. presumption that all generator bus voltages range from 0.95 to 1.1 pu. MATLAB has been used to accomplish this strategy. Each case under investigation has 05 test runs. For PSO, $C_1$=2 & $C_2$=2, $w_1$=0.4 & $w_2$=0; For GSA, α=10 and $G_0$=100; For combined PSO-GSA, $C_1$=2 & $C_2$=2, α=20, and $G_0$ =1 are taken. total number of agents (A) =25 and maximum iteration number ($t_{max}$)=50, for all case studies.

**Objective function:** By changing the inputs to the mathematical process, it should be feasible to determine the minimum or maximum output in OPF issues. This mathematical operation or function is known as a "objective function" or a "fitness function."

| Control Variables | | Case-1 (Reduction in Fuel Cost) | | | Case-2 (reduction in fuel cost & improving the voltage profile) | | | Case-3 (reduction in fuel cost & reduce the real power losses) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Initial** | **PSO** | **GSA** | **PSO-GSA** | **PSO** | **GSA** | **PSO-GSA** | **PSO** | **GSA** | **PSO-GSA** |
| $P_{G1}$ (MW) | 99.22 | 180.67 | 181.92 | 180.55 | 184.330 | 151.245 | 184.037 | 126.212 | 126.444 | 121.708 |
| $P_{G2}$ (MW) | 80 | 47.801 | 46.744 | 48.6896 | 43.2357 | 41.5886 | 50.1134 | 51.4152 | 52.4811 | 52.1241 |
| $P_{G5}$ (MW) | 50 | 20.685 | 21.381 | 20.3043 | 23.7984 | 40.9328 | 19.7210 | 28.8359 | 30.9757 | 30.8357 |
| $P_{G8}$ (MW) | 20 | 21.938 | 18.026 | 21.3278 | 20.3122 | 10.2152 | 16.9642 | 34.4099 | 34.9405 | 35 |
| $P_{G11}$(MW) | 20 | 10.000 | 12.459 | 10 | 10 | 22.9530 | 10.6306 | 30 | 22.5604 | 29.9985 |
| $P_{G13}$(MW) | 20 | 12.000 | 12.461 | 12 | 12 | 24.6029 | 13.1750 | 18.9038 | 21.9050 | 19.8951 |
| $V_{G1}$ (p.u) | 1.05 | 1.0771 | 1.0818 | 1.0779 | 1.0571 | 1.0735 | 1.0992 | 1.0311 | 1.0719 | 1.0314 |
| $V_{G2}$ (p.u) | 1.04 | 1.0571 | 1.0617 | 1.0564 | 1.0240 | 1.0401 | 1.0497 | 1.0117 | 1.0578 | 1.0176 |
| $V_{G5}$ (p.u) | 1.01 | 1.0310 | 1.0277 | 1.0238 | 1.0086 | 1.0029 | 1.0148 | 0.9753 | 1.0295 | 0.9887 |
| $V_{G8}$ (p.u) | 1.01 | 1.0332 | 1.0314 | 1.0260 | 0.9873 | 0.9760 | 0.9851 | 0.9922 | 1.0388 | 0.9922 |
| $V_{G11}$(p.u) | 1.05 | 1.0958 | 1.0061 | 1.1000 | 1.0963 | 1.0642 | 0.9789 | 1.1000 | 1.0462 | 1.1000 |
| $V_{G13}$(p.u) | 1.05 | 0.9893 | 1.0545 | 1.0888 | 1.0121 | 0.9990 | 1.1000 | 1.0464 | 1.0447 | 1.0269 |
| $T_{11}$(6-9) (p.u) | 1.078 | 1.0064 | 0.9835 | 1.0117 | 1.1000 | 0.9654 | 0.9847 | 1.1000 | 1.0173 | 1.1000 |
| $T_{12}$(6 -10) (p.u) | 1.069 | 1.1000 | 0.9794 | 0.9660 | 0.9000 | 0.9066 | 0.9054 | 0.9013 | 0.9921 | 0.9002 |
| $T_{15}$(4-12) (p.u) | 1.032 | 0.9775 | 1.0181 | 1.0375 | 0.9612 | 0.9584 | 1.1000 | 0.9444 | 1.0086 | 0.9637 |
| $T_{36}$(28-27)(p.u) | 1.068 | 0.9572 | 0.9557 | 0.9746 | 0.9705 | 0.9213 | 0.9437 | 0.9346 | 0.9782 | 0.9000 |
| $Qc_{10}$ (MVAR) | 0 | 5 | 1.0624 | 0 | 0.7375 | 1.2297 | 0 | 4.9952 | 3.0576 | 4.9999 |
| $Qc_{12}$ (MVAR) | 0 | 5 | 3.1832 | 4.9998 | 0.0027 | 0.2689 | 0.0514 | 4.9894 | 2.2908 | 5 |
| $Qc_{15}$ (MVAR) | 0 | 0.2416 | 3.2168 | 0 | 4.5991 | 3.7707 | 0 | 5 | 1.0972 | 4.8395 |
| $Qc_{17}$ (MVAR) | 0 | 0 | 1.3528 | 1.2774 | 4.9997 | 1.5470 | 4.8400 | 5 | 2.9741 | 5 |
| $Qc_{20}$ (MVAR) | 0 | 5 | 2.6013 | 5 | 5 | 1.3943 | 0.0778 | 0 | 2.6350 | 0.0049 |
| $Qc_{21}$ (MVAR) | 0 | 0 | 2.0604 | 2.2490 | 0.8743 | 4.2425 | 0.1071 | 3.7920 | 1.3149 | 0 |
| $Qc_{23}$ (MVAR) | 0 | 5 | 2.2407 | 0 | 5 | 1.3114 | 5 | 5 | 2.5631 | 0 |
| $Qc_{24}$ (MVAR) | 0 | 0 | 1.8826 | 5 | 1.2777 | 3.5536 | 5.0000 | 0 | 3.1997 | 0 |
| $Qc_{29}$ (MVAR) | 0 | 5 | 1.9791 | 5 | 4.5160 | 4.2858 | 0.0068 | 0 | 3.3155 | 1.0225 |
| Cost ($/h) | **901.94** | **802.25** | **801.77** | **801.34** | **808.20** | **842.01** | **806.88** | **829.06** | **825.68** | **814.03** |
| Ploss (MW) | **5.8222** | 9.7003 | 9.5948 | 9.4799 | 10.2764 | 8.13798 | 11.2416 | **5.3776** | **5.2071** | **5.1621** |
| Voltage Deviation (p.u) | **1.1496** | 0.9400 | 0.8876 | 0.9772 | **1.15618** | **1.30418** | **1.23044** | 0.89 | 1.243 | 1.0732 |

Table-I: PSO-GSA approach yields the best solution for many objective functions

It is evident from a comparison of the outcomes from the PSO, GSA, and PSO-GSA approaches that the recommended PSO-GSA methodology outperforms the other approaches in resolving different OPF concerns. This illustrates its ability to recognize superior solutions. The suggested combined PSO-GSA technique provides the best and sufficient dependable answers when compared to PSO and GSA.

## VII CONCLUSION

With the use of coupled PSO-GSA, this work effectively solves the OPF problem with various goal functions. An evaluation and testing of the suggested method was done using IEEE 30-bus systems. Based on the findings of the simulation, The hybrid PSO-GSA provides a reliable, resilient, and high-quality solution. The suggested hybrid PSO-GSA is an excellent method for effectively addressing the hard OPF problem, since it combines the advantages of both PSO and GSA. One of the most significant drawbacks of the PSO-GSA is that it requires a significant acceleration of processing in order to develop applications that are practical for use in big power systems.

## REFERENCES

[1]. Abou El Ela, A. A., Abido, M. A., and Spea, S. R., *"Optimal power flow using differential evolution algorithm,"* Electrical Engineering, Vol. 91, pp. 69–78, 2009.

[2]. Frank, S., Steponavice, I., and Rebennack, S., *"Optimal power flow: a bibliographic survey-I Formulations and deterministic methods,"* Energy System, Vol. 3, No. 3, pp. 221–258, 2012.

[3]. Frank, S., Steponavice, I., and Rebennack, S., *"Optimal power flow: a bibliographic survey-II Non-deterministic and hybrid methods,"* Energy System, Vol. 3, No. 3, pp. 259 289, 2012.

[4]. A. J. Wood and B. F. Wollenberg, "*Power Generation Operation and Control"*, Wiley and Sons, 1996.

[5]. Mirjalili, S., and Hashim, S. Z. M., *"A new hybrid PSOGSA algorithm for function optimization"* International Conference on Computer and Information Application (ICCIA 2010), pp. 374–377, Tianjin, China, 3–5 December 2010.

[6]. Mirjalli, S., Hashim, S. Z. M., and Sardroudi, H. M., *"Training feedforward neural networks using hybrid particle swarm and gravitational search algorithm"* Applied Mathematics Computation Vol. 218, pp. 11125–11137, 2012.

[7]. Abido, M. A.at all, *"Optimal power flow using particle swarm optimization,"* Electrical Power Energy System, Vol. 24, pp. 563–571, 2002.

[8]. Rashedi E., Nezamabadi-pour H., and Saryazdi S. *"GSA: A gravitational search algorithm,"* Information Science, Vol. 179, pp. 2232–2248, 2009.

[9]. Esmat Rashedi, Hossien Nezamabadi-pour, Saeid Saryazdi, Malihe M. Farsangi. "*Allocation of Static Var Compensator Usin Gravitational Search Algorithm"* First Joint Congress on Fuzzy and Intelligent Systems Ferdowsi University of Mashhad. 2007: 29-31.

[10]. S S. Duman, U. Güvenç, N. Yörükeren. "*Gravitational Search Algorithm for Economic Dispatch with Valve-point Effects "International* Review of Electrical Engineering. 2005; 5(6): 2890-2895.

[11]. Purwoharjono, Ontoseno Penangsang, Muhammad Abdillah dan Adi Soeprijanto. "*Voltage Control on Java-Bali 500kV Electrical Power System for Reducing Power Losses Using Gravitational Search Algorithm"*. International Conference on Informatics and Computational Intelligence (ICI). 2011: 11-17.

[12]. Serhat Duman, Yusuf Sonmez, Ugur Guvenc, dan Nuran Yorukeren *"Application of Gravitational Search Algorithm for Optimal Reactive Power Dispatch Problem"*. IEEE. 2011.

[13]. Purwoharjono, Muhammad Abdillah, Ontoseno Penangsang, Adi Soeprijanto, *"Optimal Placement and Sizing of Thyristor-controlledseries-capacitor using Gravitational Search Algorithm***"** TELKOMNIKA Indonesian Journal of Electrical Engineering Vol.10, No.5, September 2012, pp. 891~904.

[14]. Mirjalili, S., and Hashim, S. Z. M., *"A new hybrid PSOGSA algorithm for function optimization,"* International Conference on Computer and Information Application (ICCIA 2010), pp.374–377, Tianjin, China, 3–5 December 2010.

[15]. Mirjalli, S., Hashim, S. Z. M., and Sardroudi, H. M., *"Training feedforward neural networks using hybrid particle swarm and gravitational search algorithm,"* Applied Mathematics Computation, Vol. 218, pp. 11125–11137, 2012.

[16]. Roy, P. K., and Paul, C., *"Optimal power flow using krill herd algorithm,"* Int. Trans. Electrical Energy System, DOI: 10.1002/etep.1888, 2014.

[17]. Bouchekara, H. R. E. H., Abido, M. A., and Boucherma, M., *"Optimal power flow using teaching–learning-based optimization technique,"* Electrical Power System Res., Vol. 114, pp. 49–59, 2014.