International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

A Review on Load Frequency Control Using Optimization Algorithm

Shaik Sanuwar [*]

[*]Department of Electrical and Electronics Engineering, GMR Institute of Technology, Vizianagaram District, A.P, India

A B S T R A C T

Load frequency control has been a major problem in the power system. Maintaining the balance between generated power and load demand is our primary goal, without change in frequency and tie-line power. This paper deals with differential evolution algorithm, quasi-oppositional grey wolf optimization algorithm based optimizing technique. The results are compared with each other and observed which algorithm is efficient.

Keywords: Differential Evolution; Quasi-Oppositional Grey Wolf Algorithm; Load Frequency Control; Power System.

1.INTRODUCTION

Power system stability demands that total generation, total load demand, and associated system losses be balanced. When the generation of loads matches the demand for loads, a power system operates continuously. The output of each generator in a power plant that is connected to a power system via a load frequency control (LFC) system is maintained in order to balance these two parameters. The frequency reveals how well the system is balanced; if it rises, more load is being generated, which prompts the machines to run faster, and if it falls, more load is being consumed, which prompts the generators to run slower. Unpredictable load changes result in mismatches between load generation and load demand, variations in frequency and tie line interchange schedules, and system instability.[1] A power system introduces the load frequency control (LFC) phenomenon to control this. In order to maintain the target frequency and reduce system variance during transient loading conditions, LFC is used. While the allowed range for load is 10%, the allowable range for frequency fluctuation is -5 HZ to 5 HZ. Area control error occurs when the variance exceeds over its limit (ACE). A control system phenomenon is applied with an optimization approach in to reduce the ACE and optimise the system output in order to lessen the impact of this abrupt load shift. There are several optimization techniques used to tune the deviations and maintain the system output constant. There are many optimization techniques,

1. *Firefly Algorithm (FA)*
2. *Particle Swarm Optimization (PSO)*
3. *Gravitational Search Algorithm (GSA)*
4. Differential Evolution Algorithm (DE)
5. Jaya Optimization Algorithm (JO)
6. Genetic Algorithm (GA)
7. Moth Flame Optimization (MFO)
8. Quasi-Oppositional Grey Wolf Optimization Algorithm (QOGWO) etc.

In Particle Swarm Optimization (PSO) Algorithm for LFC, Separate controls are used to manage the active and reactive powers. The AVR loop modifies the voltage, whereas the LFC loop regulates the frequency and active power[1]. The two-area linked power system is simulated for step load disturbance in order to study the system frequency, tie line power flow, and system voltage. To stop any system oscillations brought on by the disturbance and restore the frequency and voltage to their nominal values is the key goal.The load frequency management issue in a single-area electrical power system that comprises of a thermal power plant with a reheat turbine and is coupled to a PV system and wind farm has been discussed in Jaya Optimization Technique[2]. This algorithm's primary goal is to analyse and lessen the frequency of power system demand caused by linking wind farms and solar power plants. The Quasi-Oppositional Grey Wolf Optimization Algorithm uses a recently developed meta-heuristic optimization approach called grey wolf optimization that is based on the influence of the leadership hierarchy and hunting behaviour of wolves in the wild[4]. To examine the performance of two area non-reheat thermal-thermal linked power systems, the proportional-integral and proportional-integral-derivative controllers' gains were optimised using the differential evolution (DE) method[5]. Analysis depicts a load frequency control strategy for a two-area, diverse-source power system made up of non-identical power plants in the Moth Flame Algorithm (MFO). It makes use of a brand-new controller called a proportional, integral, derivative (2-DOF PID) controller[3]. Utilizing several optimization approaches, including the genetic algorithm (GA) and cuckoo search algorithm, the performance of the suggested controller is first evaluated using the objective function Integral time multiplied by absolute error (ITAE) (CSA). The research shows that employing a 2-DOF PID controller is significantly more resilient than using a conventional controller for the proposed system. In Genetic Algorithm,*two robust decentralized control design methodologies* for load frequency control (LFC) are proposed[4]. The first one is based on control design using linear matrix inequalities (LMI) technique in order to obtain robustness against uncertainties. The second controller has a simpler structure, which is more appealing from an implementation point of view, and it is tuned by a proposed novel robust control design algorithm to achieve the same robust performance as the first one. More specifically, genetic algorithms (GAs) [5]optimization is used to tune the control parameters of the proportional-integral (PI) controller subject to the constraints in terms of LMI. Hence, the second control design is called GALMI. Both proposed controllers are tested on a three-area power system with three scenarios of load disturbances to demonstrate their robust performances.

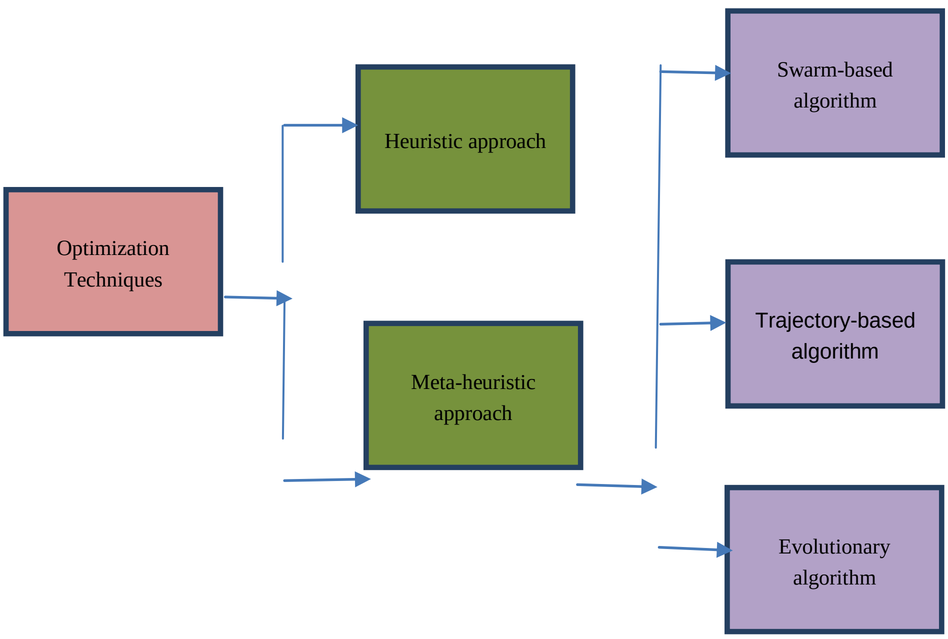


Fig :optimization Techniques

Differential Evolution algorithm:

Differential Evolution algorithm is a population based stochastic optimization algorithm. Advantages of DE are: simplicity, efficiency and real coding, easy use, local searching property and speediness. DE works with two populations; old generation and new generation. The optimization process is conducted by means of three main operations: mutation, crossover and selection.[6] In each generation, individuals of the current population become target vectors. For each target vector, the mutation operation produce a mutant vector, by adding the weighted difference between two randomly chosen vectors to a third vector. The crossover operation generates a new vector, called trial vector, by mixing the parameters of mutant vector with those of the target vector. If the trial vector obtains a better fitness value than the target vector, then the trial vector replaces the target vector in the next generation[1].

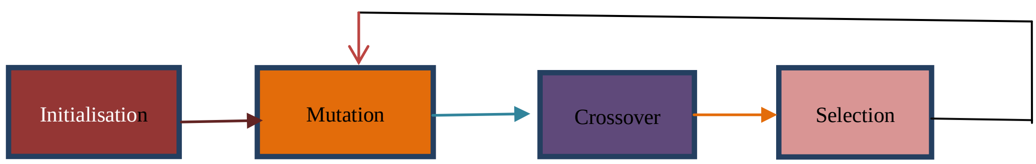


Fig : steps of DE

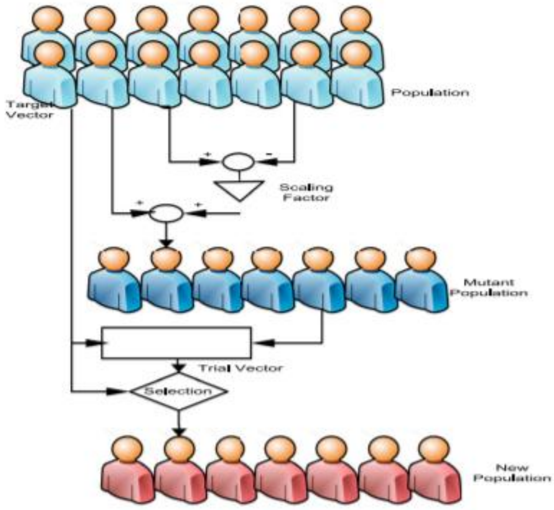


Fig Differential Evolution Algorithm

A. Initialization

B. A population of "np" is randomly initiated at the beginning of the DE process. As stated in (1) [12], thei_{th} population vector (Pop) at the present generation (g) is indicated[1].

C. $Pop_{i,g} = [Pop_{1,i,g}, Pop_{2,i,g}, \dots\dots\dots.., Pop_{d,i,g}]$ (1)

D. The initial parameter values were chosen at random and are constrained to the range $[Pop_{i,max}, Pop_{i,min}]$(2) represents the maximum and lowest border values (3).

$Pop_{i,max} = [Pop_{1,max}, Pop_{2,max}, \dots\dots\dots.., Pop_{d,max}]$ (2)

E. $Pop_{i,min} = [Pop_{1,min}, Pop_{2,min}, \dots\dots\dots.., Pop_{d,min}]$ (3)

F. Therefore, the j_{th} component of the i_{th} vector is initialized as stated by (4) [12]

G. $Pop_{j,i} = Pop_{j,min} + rand_{i,j}[1].(Pop_{j,max} - Pop_{j,min})$ (4)

H. Where, $0 < rand_{i,j} \leq 1$

I. **Mutation**

J. Three random vectors are chosen from the current population vector [1]$Pop_{ri,g}$ $Pop_{r1,g}$ $Pop_{r2,g}$and$Pop_{r3,g}$. The range$[1, n_p]$is used to generate the random indicesr_1, r_2, r_3. Any two vectors' differences are scaled by the scalar parameter F[6]. (calIed as mutant vector). The donor vector $v_{i,g}$ is created by adding this difference to the third randomly chosen vector [12]. The donor vector is shown by the equation

K. $v_{i,g} = Pop_{r1,g} + F * (Pop_{r2,g} - Pop_{r3,g})$.

L. where F is a mutation constant with a value between [0, 2]

M. Crossover

N. The crossover procedure is employed to magnify population variance. The target vector and the donor vector trade off their components to create the trial population vector, which is depicted by (6) [12].

O. $U_{i,g} = [u_{1,i,g}, u_{2,i,g} \dots\dots\dots\dots\dots, u_{d,i,g}]$ (6)

P. The range of the probability crossover ratio (CR), which is represented by the trial vector, is [0, 1], and it is represented by (7) [12].

Q. $U_{j,i,g} = \begin{pmatrix} v_{j,i,g} \text{ } if \text{ } rand_{j,i} \leq CR \text{ } or \text{ } j = I_{rand} \\ Pop_{j,i,g} \text{ } otherwise \end{pmatrix}$(7)

R. Where I_{rand} is an integer that can be anything between [1, 2........., d]. d is the variable's dimension in this case.

S.

T.

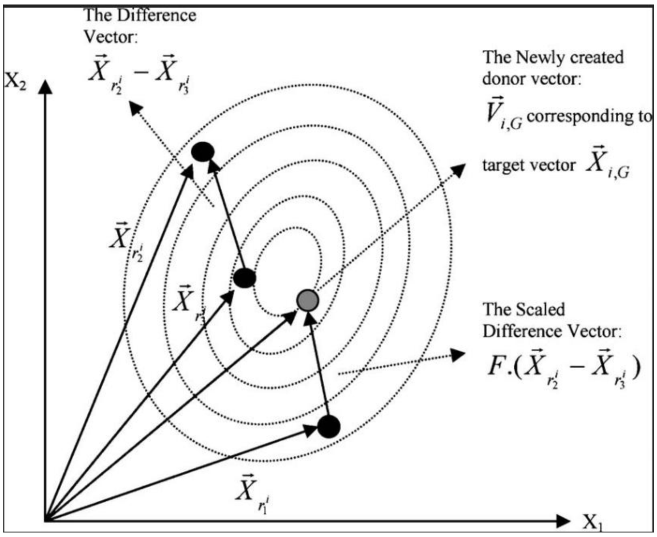


Fig DE Mutation scheme in space

D. **Selection**

The selection procedure is then carried out to determine the target's condition or the trial vector for the following generation. This method guarantees that the overall population size stays constant. In (8) [12], the selecting process is detailed.

$$Pop_{i,g+1} = \begin{pmatrix} U_{i,g+1} \ if \ f\left(U_{i,g+1} \leq f\left(Pop_{i,g}\right)\right) \\ Pop_{i,g} \ \ otherwise \end{pmatrix} \quad (8)$$

3.GRAY WOLF ALGORITHM

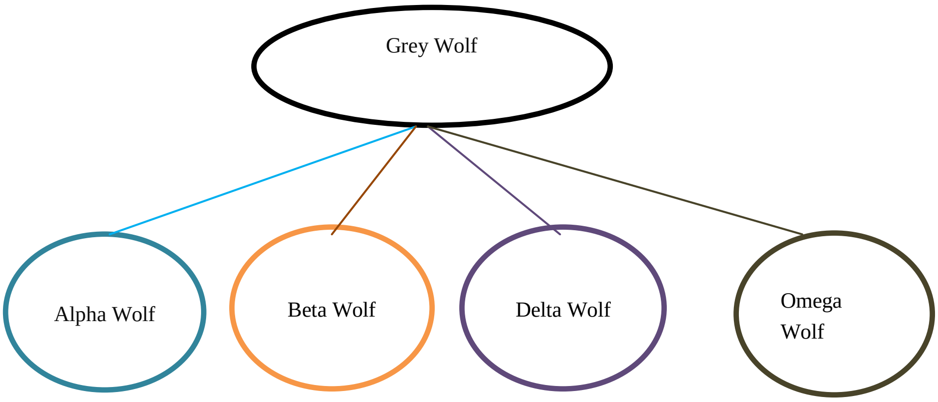
GWO is a metaheuristic proposed by Mirjaliali Mohammed and Lewis, 2014. GWO is inspired by the social hierarchy and the hunting technique of Grey Wolves. Metaheuristic means high level problem independent algorithm framework. It finds the best solution out of all possible solutions of an optimization[7].

1. Who are grey wolves?

Grey Wolf is also known as Gray wolf, it is a large canine. It runs at a speed of50-60 km/h. They live in a highly organized packs.

	MALE WOLF	FEMALE WOLF
Weight	40kg	37kg
Length	105cm – 160cm	80cm – 85cm
Height	41inch – 63inch	31inch – 33inch

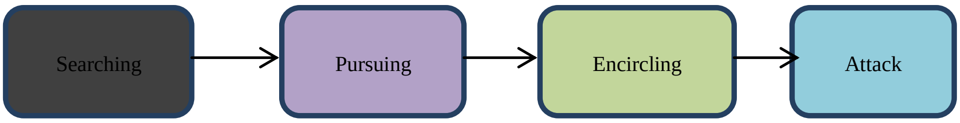
Table: Specifications of gray wolf



Fg : Classifications of Grey wolf

The Alphas (a male and a female) are the leader of the pack. Other members of the pack follows Alphas[2]. Alpha wolf is responsible for making decision about hunting, sleeping places, time to wake up and other. Second level of Grey wolf hierarchy is Beta Wolf. Best candidate to be alpha wolf. Beta wolf helps the alpha wolf in decision making and [8]Omega then it is a Delta Wolf. Delta wolf dominates Omega wolf. Delta wolf work for pack in case of any danger. They provide food to the pack. Lowest ranking Grey wolf is Omega Wolf. Omega wolf plays the role of scapegoat (Victim – who is blamed for the mistakes or faults of other). Scouts, Elders, Hunters and Caretakers belongs to this category. They are last wolves allows to eat. Grey wolf Optimization algorithm mimic the Leadership and Hunting mechanism of grey wolves. Main steps of grey wolf hunting are:[8]

1. Searching for the Prey.
2. Tracking, Chasing and Approaching the Prey.
3. Pursuing, Encircling and Harassing the Prey until it stop moving.
4. Attacking the Prey.



Fug steps of grey wolf

Mathematical Model of GWO Algorithm

Alpha is regarded as the best fit option for simulating the social behaviour of the grey wolf, followed by beta and delta, respectively, while the other alternatives are categorised under omega. In GWO, alpha, beta, and delta direct the hunting (optimization) process, whereas omega always follows these three wolves. Encircling the Prey[2]. Grey wolves Encircle the prey during hunting. Encircling behavior is modeled as:

$$D = \overrightarrow{\left|\vec{C}.x_P(t) - \vec{x}(t)\right|} \qquad (1)$$

$$\vec{x}(t+1) = \overrightarrow{x_p(t) - \vec{A}\vec{D}} \qquad (2)$$

Where, t = current iterations, $\overrightarrow{x_p}$ = position of the prey, $\vec{x}$ = position of grey wolf, $\vec{A}.\vec{C}$ = coefficient vectors

$\vec{A}, \vec{C}$ vectors are calculated as:

$$\vec{A} = 2\vec{a} * \overrightarrow{r_1} - \vec{a} \qquad (3)$$

$$\vec{C} = 2\overrightarrow{r_2} \qquad (4)$$

where, $\overrightarrow{r_1}$and $\overrightarrow{r_2}$ are two random vectors between [0, 1] and the component of $\vec{a}$ is linearly decreasing from 2 to 0 over each course of the iteration.

The locations of the grey wolves are updated during the hunting phase, which is mostly controlled by the alphas. Even though alphas are the primary agents during the hunting phase, betas and deltas may also take part in the hunt[3]. We now know the potential alpha, beta, and delta solutions for grey wolves, however we are unsure of the precise or ideal prey location. The three best answers (so far) in terms of alpha, beta, and delta are kept, and the remaining solutions, including omega, compete to determine the optimum placements. To update the wolf locations surrounding the prey, the following formulae are utilised [40].

$$\overrightarrow{D_\alpha = \left|\vec{C}_1 \overrightarrow{X_\alpha - \vec{X}}\right|}$$

$$\overrightarrow{D_\beta = \left|\vec{C}_2 \overrightarrow{X_\beta - \vec{X}}\right|}$$

$$\overrightarrow{D_\delta = \left|\vec{C}_3 \overrightarrow{X_\delta - \vec{X}}\right|}$$

$$\overrightarrow{X_1 = \overrightarrow{X_\alpha - \overrightarrow{A_1(\overrightarrow{D_\alpha})}}}$$

$$\overrightarrow{X_2 = \overrightarrow{X_\beta - \overrightarrow{A_2(\overrightarrow{D_\beta})}}}$$

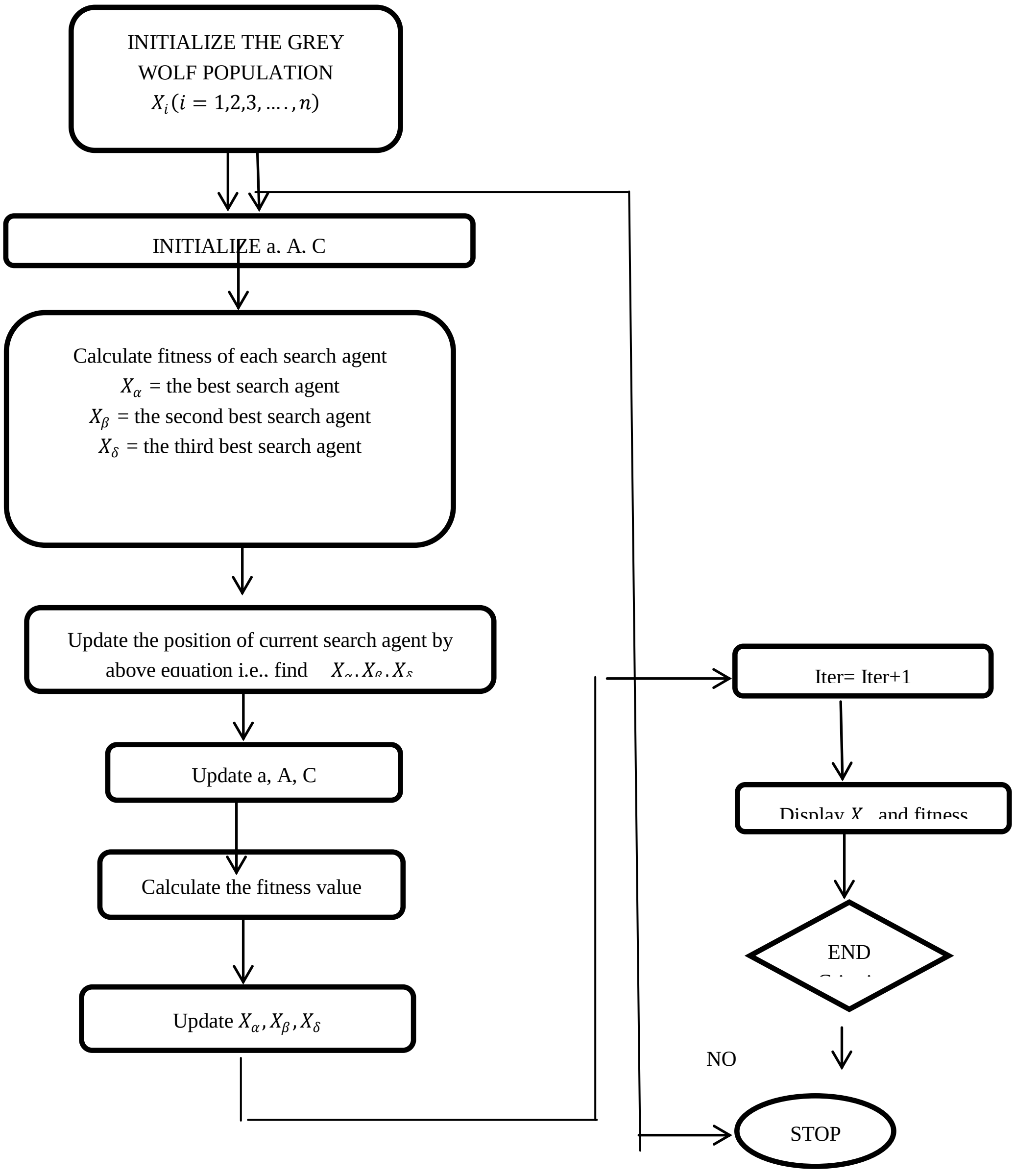
$$\overrightarrow{X_3 = \overrightarrow{X_\delta - \overrightarrow{A_3(\overrightarrow{D_\delta})}}}$$

$$\overrightarrow{X_{(t+1)=\frac{\overrightarrow{X_1+\overrightarrow{X_2+\overrightarrow{X_3}}}}{3}}}$$

Exploitation describes the capacity to conduct local searches in and around the potential areas found during the exploration stage. The grey wolves end their hunt by attacking their victim when it stops moving, as mentioned in the sections above. Two parameters, as stated below, are taken into account in order to mathematically define the model approaching the prey. From 2 to 0, $\vec{a}$ decreases linearly, and this causes the fluctuations of $\vec{A}$ to diminish as well. Alternatively stated, $\vec{A}$ is a random number between $\frac{1}{2}$a; a: The next position of the search agent can be anywhere between the present position and the position of the prey when the random value of $\vec{A}$ is between [1, 1].

The positions of alpha, beta, and delta provide the foundation for the grey wolf algorithm's optimal search. When looking for prey, they split from one another, and when attacking the victim, they converge. In mathematics, the search agent diverges to the prey when the random value of $\vec{A}$ is bigger than 1 or less than -1. This highlights the GWO algorithm's exploratory tendency. $\vec{C}$ is a further variable in the GWO approach that aids in the exploration process. According to (4), the random value of $\vec{C}$ changes between [0,2], which has an impact on the difficulty of determining the distance as in (1). As a result, GWO exhibits more erratic behaviour throughout the optimization, promoting exploration and avoiding local optima[3].

4. GWO FLOWCHART



10.RESULTS ANDDISCUSSION:

Optimi zati- on	Performance			Advantage	Weakness	Suggesti-on
	Min Fitness	**Ave Fitness**	**Ave Time**			
GA	Contain 5/10 best minimum fitness	Contain 3/10 best average fitness	Contain 10/10 faster than DE and PSO.	If suitable operation techniques were implemented, GA can be terminated faster and performance can be increased. The diversity of chromosome was increased by using breeding operations.	Generation update • Whole population will be replaced with next generation chromosome • The best solution can only be found from the global optimum. Hence, did not have a stable result. Steady state update	Some new genetic values should be introduced into the population without increasing too much time for GA in searching optimum result.
DE	Contain 2/10 best minimum fitness	Contain 3/10 best average fitness	Contain 10/10 faster than PSO.	Performed better to GA. Using combination of the same population chromosome in forming a new generation.	Probably none of previous generation chromosomes are carried forward to the next generation. However, better result can be produced Crossover and mutation operation were performed as one process.	If crossover and mutation operation were not performed, let the chromosome learned towards global optimum.
PSO	Contain 3/10 best minimum fitness	Contain 6/10 best average fitness	Contain 0/10 faster than DE and GA.	Velocity and position value can be controlled by using velocity clamping parameter. Easier to be implemented compared to GA. Less number of parameters to be tuned compared to GA.	Too much depending on global best position. Previous velocity and best position were referred will make the particle position value increasing and moving away from the global best position and optimum results.	Decrease number of parameters usage.

In this study, the conventional PI or PID controllers' gains have been optimised using the DE optimization technique (taken one step at a time) for frequency stabilisation. Additionally, the quasi-oppositional grey wolf optimization algorithm, a novel nature-inspired optimization technique, has been used to increase the dynamic stability of an interconnected power system. Last but not least, sensitivity analysis demonstrates that the improved QOGWO based PID-controller is highly resilient and provides acceptable performance under uncertainty.

REFERENCES :

[1]. A. S. L. V. Tummala, H. K. R. Alluri, and P. V. Ramanarao, "Optimal Control of DFIG Wind Energy System in Multi-machine Power System using Advanced Differential Evolution," IETE J. Res., vol. 66, no. 1, pp. 91–102, 2020, doi: 10.1080/03772063.2018.1466732.

[2]. A. S. L. V. Tummala and R. K. Inapakurthi, "A Two-stage Kalman Filter for Cyber-attack Detection in Automatic Generation Control System," J. Mod. Power Syst. Clean Energy, vol. 10, no. 1, pp. 50–59, 2022, doi: 10.35833/MPCE.2019.000119.

[3]. S. Kumari, G. Shankar, S. Gupta, and K. Kumari, "Study of load frequency control by using differential evolution algorithm," 1st IEEE Int.

Conf. Power Electron. Intell. Control Energy Syst. ICPEICES 2016, pp. 1–5, 2017, doi: 10.1109/ICPEICES.2016.7853508.

[4]. M. H. Fini, G. R. Yousefi, and H. H. Alhelou, "Comparative study on the performance of many-objective and single-objective optimisation algorithms in tuning load frequency controllers of multi-area power systems," IET Gener. Transm. Distrib., vol. 10, no. 12, pp. 2915–2923, 2016, doi: 10.1049/iet-gtd.2015.1334.

[5]. M. I. A. E. Ali, A. A. Z. Diab, and A. A. Hassan, "Adaptive Load Frequency Control Based on Dynamic Jaya Optimization Algorithm of Power System with Renewable Energy Integration," 2019 21st Int. Middle East Power Syst. Conf. MEPCON 2019 - Proc., vol. 0, pp. 202–206, 2019, doi: 10.1109/MEPCON47431.2019.9007955.

[6]. N. E. Y. Kouba, M. Menaa, M. Hasni, and M. Boudour, "Optimal control of frequency and voltage variations using PID controller based on particle swarm optimization," 2015 4th Int. Conf. Syst. Control. ICSC 2015, pp. 424–429, 2015, doi: 10.1109/ICoSC.2015.7152777.

[7]. A. Sahu and S. K. Hota, "Performance comparison of 2-DOF PID controller based on Moth-flame optimization technique for load frequency control of diverse energy source interconnected power system," Int. Conf. Technol. Smart City Energy Secur. Power Smart Solut. Smart Cities, ICSESP 2018 - Proc., vol. 2018-January, pp. 1–6, 2018, doi: 10.1109/ICSESP.2018.8376686.

[8]. Manoj, V., Sravani, V., Swathi, A. 2020. A multi criteria decision making approach for the selection of optimum location for wind power project in India. EAI Endorsed Transactions on Energy Web, 8(32), e4

[9]. J. T. Bialasiewicz, "Renewable energy systems with photovoltaic power generators: Operation and modeling," IEEE Trans. Ind. Electron., vol. 55, no. 7, pp. 2752–2758, Jul. 2008

[10]. MNRE (Ministry of New and Renewable Energy), Grid Connected Power/Solar. 2018.

[11]. S. Kouro, J. I. Leon, D. Vinnikov, and L. G. Franquelo, "Grid-connected photovoltaic systems: An overview of recent research and emerging PV converter technology," IEEE Ind. Electron. Mag., vol. 9, no. 1, pp. 47–61, Mar. 2015.

[12]. Dinesh, L., Sesham, H., & Manoj, V. (2012, December). Simulation of D-Statcom with hysteresis current controller for harmonic reduction. In 2012 International Conference on Emerging Trends in Electrical Engineering and Energy Management (ICETEEEM) (pp. 104-108). IEEE

[13]. Manoj, V. (2016). Sensorless Control of Induction Motor Based on Model Reference Adaptive System (MRAS). International Journal For Research In Electronics & Electrical Engineering, 2(5), 01-06.

[14]. V. B. Venkateswaran and V. Manoj, "State estimation of power system containing FACTS Controller and PMU," 2015 IEEE 9th International Conference on Intelligent Systems and Control (ISCO), 2015, pp. 1-6, doi: 10.1109/ISCO.2015.7282281

[15]. Manohar, K., Durga, B., Manoj, V., & Chaitanya, D. K. (2011). Design Of Fuzzy Logic Controller In DC Link To Reduce Switching Losses In VSC Using MATLAB-SIMULINK. Journal Of Research in Recent Trends.

[16]. Manoj, V., Manohar, K., & Prasad, B. D. (2012). Reduction of switching losses in VSC using DC link fuzzy logic controller Innovative Systems Design and Engineering ISSN, 2222-1727

[17]. Dinesh, L., Harish, S., & Manoj, V. (2015). Simulation of UPQC-IG with adaptive neuro fuzzy controller (ANFIS) for power quality improvement. Int J Electr Eng, 10, 249-268

[18]. Manoj, V., Swathi, A., & Rao, V. T. (2021). A PROMETHEE based multi criteria decision making analysis for selection of optimum site location for wind energy project. In IOP Conference Series: Materials Science and Engineering (Vol. 1033, No. 1, p. 012035). IOP Publishing.

[19]. Kiran, V. R., Manoj, V., & Kumar, P. P. (2013). Genetic Algorithm approach to find excitation capacitances for 3-phase smseig operating single phase loads. Caribbean Journal of Sciences and Technology (CJST), 1(1), 105-115.

[20]. Manoj, V., Manohar, K., & Prasad, B. D. (2012). Reduction of Switching Losses in VSC Using DC Link Fuzzy Logic Controller. Innovative Systems Design and Engineering ISSN, 2222-1727.

[21]. Manoj, V., Krishna, K. S. M., & Kiran, M. S. Photovoltaic system based grid interfacing inverter functioning as a conventional inverter and active power filter.