Frequency control in hybrid distributed power systems via type-2 fuzzy PID controller

Rajendra Kumar Khadanga1 | Amit Kumar2 | Sidhartha Panda3

1 Department of Electrical and Electronics Engineering, CUTM, Bhubaneswar 752050, India
2 Department of Electrical and Instrumentation Engineering, TIET, Patiala 147004, India
3 Department of Electrical Engineering, VSSUT, Burla, Odisha 768018, India

Correspondence
Rajendra Kumar Khadanga, Department of Electrical and Electronics Engineering, Centurion University of Technology and Management, Bhubaneswar 752050, India
Email: rajendra697@gmail.com

Abstract
In this research article, a novel approach is proposed by considering a modified equilibrium optimization (MEO) algorithm based “interval type-2 fuzzy proportional integral derivative (IT2FPID) controller” for the load frequency control of the multi-area hybrid power system. The performance of the modified algorithm is tested by comparing it with the standard EO algorithm considering various standard benchmark test functions. Further, the efficacy of the MEO algorithm is tried by planning an IT2FPID controller for frequency regulation of the said hybrid system. The supremacy of the MEO-based IT2FPID controller is introduced by comparing its outcomes with MEO-based T1FPID structure, MEO-based conventional PID and EO-based PID controller techniques. It is observed that the MEO-based IT2FPID controller is more effective compared to others.

1 INTRODUCTION
The standard assignment of load frequency control (LFC) is to guarantee the frequency deviations inside the allowable range [1]. This major task identified with LFC is fundamental in a well-designed power system to keep up the system frequency and voltage inside a permissible limit [2]. LFC can be considered as a supervisory control system that maintains a power balance between the generation and the load demand thus maintains the system frequency as well as and tie-line power. From the literature study, it is seen that in the past numerous researches were done and attempted to tackle the LFC issue, which maintains scheduled frequency and tie-line power exchanged in normal as well as under system disturbed conditions [3, 4]. Another observation can be taken from the literature that, the vast majority of the current research on LFC is centred around the frequency control of an interconnected power system however none of them have considered the effect of distributed energy sources on the LFC plan [5]. Few of them have considered the effect of thermal and DG for LFC application however not many investigates on the interconnection of the hydropower system with DG [6]. Thus, this paper proposes the effect of DG in the hydro-thermal environment, which forms a hybrid distributed two-area power system.

The frequency regulation of the AGC is a significant factor [7, 8] and accomplishing this distinctive strategy was proposed [9, 10]. FLC is one approach that can deal with the uncertainties and dynamic performance of the AGC [11]. The different FLC-based controllers which are explained in the literature review are hPSO-PS based FLC [12], ICA-based fuzzy PID with a subsidiary channel (FPIDN)/fluffy PIDN-FOI [13], BFOA tuned fractional-order fuzzy PID [14] and back-propagation and gradient descent based adaptive type-2 fuzzy control is demonstrated [15].

Another approach to take care of the frequency regulation issue is to utilize the evolutionary algorithm (EA) and is successfully utilized to manage the non-linear functions associated with LFC design [16]. The various application of EA area bacteria foraging optimization [17], bat algorithm [18], particle swarm optimization [19], genetic algorithm [20], cuckoo search algorithm [21] and firefly algorithm [22], gravitational search algorithm [23, 24], water cycle algorithm [25], base optimization algorithm [26]. Despite the way that these methods give a predominant execution and dealing with compelling LFC structure, their rate of convergence is slow and always trapped into local optima.

In recent years, the optimization algorithm called equilibrium optimizer (EO) has been broadly utilized in numerous
The concept behind this algorithm is the mass balance model which maintains a balance between dynamic and equilibrium states. In this algorithm, each particle behaves as a search agent in which the particle and its concentration are considered as a solution and position respectively. The final best solution can be achieved by randomly updating the particle’s concentration known as equilibrium optimization [28]. Even though the equilibrium optimizer algorithm has been generally utilized, yet it additionally has a few deformities. The biggest problem associated with EO is, it easily falls into the local optimum [29]. Thus, in this article, the EO algorithm is further improved by introducing some scaling factors which control the movement of particles during the conventional EO algorithm. Thus, in this paper a new strategy is proposed in which a novel modified equilibrium optimization (MEO) algorithm is utilized which can tune the interval type-2 fuzzy proportional integral derivative (IT2FPID) controller.

The contribution in this paper are quickly depicted as:

- An interval type-2 fuzzy proportional integral derivative (IT2FPID) controller is proposed to archive the frequency control issue of a two-area hybrid power system.
- The two-area hybrid power system is basically the integration of some distributed energy sources and some conventional energy sources.
- A novel modified equilibrium optimization algorithm (MEO) is proposed by introducing some scaling factor in the original EO Algorithm.
- The MEO algorithm is tested over EO and some conventional algorithms like MWAO and WOA algorithm in terms of fitness function are compared utilizing different benchmark functions.
- The impact of MEO-based Interval type-2 fuzzy PID controller in the said hybrid system is investigated and is compared with type-1 fuzzy PID and some standard controller and observed better frequency regulation.

The proposed research work is organized into seven major sub-sections. The modelling of the different system components of the power system is described in section II. Section III demonstrates the structure of the IT2FPID controller for the proposed study and the problem formulation for the above system is described in Section IV. The brief idea of the developed EO algorithm and its modified version is explained in section V. Section VI represents the simulation results and discussion by considering the different disturbances of the system. Finally, Section VIII represents the conclusions for the above study.

# 2 | DETAILS OF SYSTEM UNDER STUDY

Figure 1 shows a hybrid power system comprising of a thermal power plant unit, hydropower system with various DG sources [6, 10, 16]. The DG system contains sources like HAE, WTG, FC, DEG, MTG, BESS etc. Table 1 shows a set of nominal parameters in terms of gain (K) and time constant (T) for the said hybrid power system [30–38].

## 2.1 Mathematical modelling of generating units

### 2.1.1 Wind turbine generator

The wind turbine system has several non-linearities which include a pitch system. The property of the wind turbine is that, as the wind speed changes the pitch angle also changes, thereby introducing non-linearity. The wind turbine is portrayed by non-dimensional curves of power coefficient $C_p$ as an element of both tip speed proportion $\lambda$ and blade pitch point $\beta$. The tip speed proportion, which is characterized as the proportion of the speed at the blade tip to the wind speed, can be communicated by [30]:

$$\lambda = \frac{R_{blade} \omega_{blade}}{V_w}$$  \hspace{1cm} (1)

where $R_{blade}$ shows the radius blades and $\omega_{blade}$ shows the speed of blades. The articulation for approximating $C_p$ as an element of $\lambda$ and $\beta$ is given by:

$$C_p = (0.44 - 0.0167\beta) \sin \left( \frac{\Pi (\lambda - 3)}{15 - 0.3\beta} \right) - 0.0184 (\lambda - 3) \beta$$  \hspace{1cm} (2)

The expression for the output power of the wind turbine is:

$$P_{WTG} = \frac{1}{2} \rho A_t C_p V_w^3$$  \hspace{1cm} (3)

where $\rho$ shows the air density and $A_t$ represents the swept area of blades.

Consequently, for low-frequency oscillation, it is spoken by a first-order transfer function as [31]:

$$G_{WTG}(s) = \frac{K_{WTG}}{1 + sT_{WTG}}$$  \hspace{1cm} (4)

### 2.1.2 Hydrogen aqua-electrolyser

The HAE is utilized for creating hydrogen (H₂) employing water electrolysis utilizing the power and putting away H₂ during typical operation. The transfer functions of HAE can be represented as [32]:

$$G_{HAE}(s) = \frac{K_{HAE}}{1 + sT_{HAE}}$$  \hspace{1cm} (5)

### 2.1.3 Fuel cell

Fuel cell acts as a vital component because of its reduced pollution and increased efficiency. The fuel cell generator is a higher-order system but for the small frequency 1st order transfer function is taken [33]:

$$G_{FC}(s) = \frac{K_{FC}}{1 + sT_{FC}}$$  \hspace{1cm} (6)
2.1.4 Diesel engine generator

The DEG independently capable of supplying the shortage of power and can minimize the power imbalance between supplies and load demand. It is a non-linear system as it is having a generation constraint [34].

\[
G_{DEG}(s) = \frac{K_{DEG}}{1 + sT_{DEG}}
\]  

(7)

2.1.5 Battery energy storage system

The BESS is coupled in the control loop and is excited by the signal obtained from the controller. According to the requirement, they act as a source or load to the system. The storage elements in the power system are supposed to have rate constraints that allow the components to work in the non-linear zone. Also, the rate constraint helps to manage the electromechanical characteristics displayed by the elements and prevents the mechanical shock due to sudden frequency
Table 1: Nominal parameters of the components of the hybrid power system

| Components                      | Gain (K)       | Time constant (T) |
|--------------------------------|----------------|------------------|
| Wind turbine generator (WTG)    | $K_{WTG} = 1$  | $T_{WTG} = 1.5$  |
| Hydro-aqua electrolyser (AE)    | $K_{AE} = 0.002$ | $T_{AE} = 0.5$   |
| Fuel cell (FC)                  | $K_{FC} = 0.01$ | $T_{FC} = 4$     |
| Diesel energy storage system (DEG)| $K_{DEG} = 0.003$ | $T_{DEG} = 2$   |
| Battery energy storage system (FESS)| $K_{BESS} = -0.01$ | $T_{BESS} = -0.1$ |
| Micro-turbine                   | $K_{MTG} = 1$  | $T_{MTG} = 1.5$  |
| Thermal power system            | $T_g = 0.08, T_i = 0.3, T_{12} = 0.0866, B = 0.425, K_g = 0.5, T_I = 10.0$ |
| Hydro power plant               | $K_g = 120, T_p = 20, R_1 = 2.4, R_2 = 2.4, K_1 = 1, T_1 = 48.7, T_2 = 0.513, T_R = 5, T_W = 1$ |

Equations (10)–(13) represent the transfer function representation of the generator, governor, turbine and reheater system respectively.

2.1.8 Modelling of hydro-power plant

The transfer function of mechanical ‘hydraulic governor’ and ‘hydro turbine’ of the hydro plant are given by [38]:

$$G_{HG}(s) = \left[ \frac{K_1}{1 + sT_1} \right] \left[ \frac{1 + sT_R}{1 + sT_2} \right]$$ (14)

$$G_{HR}(s) = \frac{1 + sT_W}{1 + 0.5 \times sT_W}$$ (15)

where $T_1, T_R, T_2$ and $T_W$ represent the speed governor, reset time, the time constant, starting time of water in the penstock of the hydro plant respectively.

2.1.9 Modelling of power system and load

The transfer function of the combined power system with load is given by:

$$G_p(s) = \frac{K_p}{1 + sT_p}$$ (16)

3 | STRUCTURE OF PROPOSED INTERVAL TYPE-2 FUZZY LOGIC PID CONTROLLER (IT2FPID)

3.1 Background

Type-2 fuzzy sets (T2FSs) were proposed as an extension to type-1 fuzzy sets (T1FSs), which can handle uncertainties present in T1FSs. The principal difference between a T2FS and a T1FS is that the membership functions are not crisp numbers rather they are fuzzy sets. These fuzzy sets are also known as secondary membership functions (MF) and when these become a unit interval for the primary membership function, it is termed as interval type-2 fuzzy set (IT2FS). A fuzzy system that uses, in any event, one IT2FS in the predecessor or subsequent piece of its rule base is known as an "interval type-2 fuzzy logic system (IT2FLS)" [39].

IT2FLSs have been utilized in a few applications, and they regularly beat their type-1 partners when dealing with uncertainties. The main concept behind the IT2FLS controller mainly depends upon the concept of the “type-reduction (TR) method” which deals with the conversion from T1FS before it reaches the final crisp output. The T1FS can be considered as an output of the IT2FLS. Initially, TR was performed utilizing the iterative Karnik–Mendel (KM) method and some different strategies which are computationally concentrated and...
non-iterative. In this manner, the best technique for the TR can be considered as a genuine issue.

In this paper, two option portrayals for IT2FLSs have been proposed and they are known as Coupland and John’s Geometric Centroid and the Nie-Tan strategy. Coupland and John’s Geometric Centroid (GC) defuzzification gives a decent guess to the TR method. One of the qualities of utilizing the GC strategy is that the two ramifications activities performed to locate the upper and lower limits of the subsequent IT2FS are free from each other and can be performed simultaneously, and type-1 fuzzy operations can be used in doing such. We acquaint a methodology with arriving at a closed-form numerical portrayal for IT2FLSs dependent on the GC strategy. We additionally stretch out the outcomes to give another form mathematically dependent on the Nie-Tan administrator.

Now the main steps for designing the IT2FPID controller are knowledge-based design, control tuning parameters and membership function. One way of designing an IT2FPID controller is the online tuning of membership function which needs a heavy computation and makes the system complicated. Another way of designing an IT2FPID controller is to use a PID controller and optimize the input scaling factors and PID gains. For the proposed IT2FPID controller, the structure and its membership functions are shown in Figure 2(A,B).

From the membership figure, it comprises of three membership functions for one input. By restricting the scope of the contribution to values $[-1, 1]$, the left and right membership functions are for all intents and purposes S and Z Gaussian.

A. Structure of proposed IT2FPID controller

B. Membership function

For the three membership functions (with values as $\mu_1 = -1$, $\mu_2 = 0$, $\mu_3 = 1$, $\Delta \mu = 1/8$, and $\sigma = 0.418$), the rough UMF is Gaussian with $\mu = 0$, and $\sigma = 0.5128$, the LMF is a downsized Gaussian, with $\mu = 0$, $0.3532$, and a scaling variable of 0.895. The membership functions are assigned linguistic variables in terms of inputs/output variables as shown in Table 2.

### 3.2 Mathematical design

An interval type-2 fuzzy set is characterized as [40]

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} f_{\mu, \sigma}(x) \, du \, dx$$

where $\tilde{A}$ represents secondary grades and its value is 1, $x \in X$ represents the primary variable, $u \in J_x$ shows the secondary variable and $f_{\mu, \sigma}$ is the primary membership of $x$.

Now the uncertain parameters $\tilde{A}$ can be formulated as the combination of the different primary function termed as FOU which can be represented by:

$$\text{FOU}(\tilde{A}) = \bigcup_{\forall x \in X} J_x = \left\{ (x, u) : \forall x \in X, \mu_{-\tilde{A}} \sim (x), \tilde{p}_{-\tilde{A}} \sim (x) \right\}$$

(18)

where

$$\mu_{-\tilde{A}} \sim (x) \equiv \text{FOU}(\tilde{A}) \quad \forall x \in X,$$

$$\tilde{p}_{-\tilde{A}} \sim (x) \equiv \text{FOU}(\tilde{A}) \quad \forall x \in X$$

shows the lower membership function (LMF) and upper membership function (UMF) of $\tilde{A}$ respectively and $J_x$ is an interval, so that FOU($\tilde{A}$) can be again represented as

$$\text{FOU}(\tilde{A}) = \bigcup_{\forall x \in X} \left[ \mu_{-\tilde{A}} \sim (x), \tilde{p}_{-\tilde{A}} \sim (x) \right]$$

(19)
4 | OPTIMIZATION PROBLEM

In the proposed paper the minimization in the change in frequency is considered as the objective, which can be achieved by using an error signal known as integral time absolute error (ITAE). ITAE objective function is associated with time which is vital in optimization and it upgrades the system output in light of time reliance, subsequently, it is generally used in the literature. The ITAE ($J$) objective function can be formulated as [41]:

$$J = ITAE = \int_0^{t_{sim}} (|\Delta F_1| + |\Delta F_2| + |\Delta P_{tie}|) \cdot t \cdot dt$$  (20)

where $\Delta F_1$ and $\Delta F_2$ represents the area 1 area 2 frequency deviations, $\Delta P_{tie}$ shows the tie-line power deviation; $t_{sim}$ the total simulation time.

Now to trace out the controller parameters an objective function can be streamlined which is represented by [42]:

Minimize $J$  (21)

Subject to

$$K_{P \text{ min}} \leq K_P \leq K_{P \text{ max}}$$

$$K_{I \text{ min}} \leq K_I \leq K_{I \text{ max}}$$

$$K_{D \text{ min}} \leq K_D \leq K_{D \text{ max}}$$

$$K_{1 \text{ min}} \leq n \leq K_{1 \text{ max}}$$

$$K_{2 \text{ min}} \leq n \leq K_{2 \text{ max}}$$  (22)

where $K_{\text{ min}}$ and $K_{\text{ max}}$ represents the smallest and largest values of the controller parameters.

5 | PROPOSED MODIFIED EQUILIBRIUM OPTIMIZATION ALGORITHM

5.1 | Equilibrium optimization algorithm (EO)

EO is an as of late newly created optimization technique whose calculation depends on sine and cosine scientific capacities. The global optimal point is gotten after a few cycles with an enormous number of irregular solutions. Advancement of this algorithm experiences in two stages. In the exploration stage a promising region is shaped with the random solutions in the arrangement set at a high rate while in the exploitation stage, the difference in random solutions and the global optimum point is moderate and acquired. The numerical displaying of sine and cosine algorithm is appeared by the refreshing positions of solutions for the two stages are spoken to by [24].

The concept of the equilibrium optimizer (EO) algorithm, its detailed mathematical description and its source of inspiration are described below. The motivation behind the EO algorithm is simple and based on the properly mixed dynamic mass-parity on a control volume which can be represented by an ordinary differential equation of 1st order and is depicted as:

$$\lambda \frac{dC}{dt} = QC_{eq} - QC + G$$  (23)

where $C$ represents the concentration within the control volume ($V$), the term $\lambda \frac{dC}{dt}$ represents the mass change rate in a control volume, The notation $Q$ is indicating the volumetric rate of outflow and inflow of the control volume, $C_{eq}$ is showing the concentration at the stage of equilibrium when there is no mass generation within control volume, and $G$ represents the rate at which mass is generated within the control volume.

When the rate of change in mass within control volume is zero it is considered as it reaches a steady equilibrium state, i.e. $\lambda \left( \frac{dC}{dt} \right) = 0$.

After rearranging the Equation (20) in terms of a control volume concentration ($C$) concerning time ‘$t$’, can be obtained as:

$$\frac{dC}{\lambda C_{eq} - \lambda C + \frac{C_{eq}}{V}} \cdot dt \equiv dt$$  (24)

Equation (22) is showing the integration of Equation (21) concerning time.

$$\int_{C_0}^C \frac{dC}{\lambda C_{eq} - \lambda C + \frac{C_{eq}}{V}} \equiv \int_{t_0}^t dt$$  (25)

The solution of Equation (22) becomes

$$C = C_{eq} + (C_0 - C_{eq})F + \frac{G}{\lambda V}(1 - F)$$  (26)

Variable $F$ in Equation (23) can be calculated as given below:

$$F = \exp[-\lambda(t - t_0)]$$  (27)

where $t_0$ shows the time and $C_0$ represents the concentration.

EO is presented below in the sub-section utilizing the above conditions as the general structure. In EO, a particle is practically equivalent to a solution and the particle’s position is closely resembling concentration for PSO algorithm as given in Equation (24). Every term and how they influence the search pattern are characterized in the following.
5.1.1 Initialization and fitness function computation

EO algorithm considers an initial population set to begin the meta-heuristics procedure, which can be expressed by:

$$C_{\text{initial}} = C_{\min} + \text{randi}(C_{\max} - C_{\min}) \quad i = 1, 2, \ldots, n$$

(28)

$C_{\text{initial}}$ represents the concentration vector at starting for the $i$th particle, $C_{\min}$ and $C_{\max}$ represents the lowest and highest values of the variables, Rand $i$ shows a random number varying in between [0, 1], and $n$ shows the population. Particle performance is evaluated based on the fitness function and then they are arranged either in ascending or descending order to obtain the equilibrium solutions.

5.1.2 Equilibrium pool and candidates ($C_{eq}$)

The balanced state is the last stage of the convergence condition of the algorithm procedure, this balanced condition is known as the global optimum. By several experiments performed and consideration of many case problems, the four equilibrium candidates are identified and these candidates provide superior investigation ability to EO, while the mean of these aids in exploitation. The fifth particle is the mean of the four equilibrium candidates. Thus, the above five candidates are used to construct a vector known as balance pool:

$$\overrightarrow{C_{eq, pool}} = \{\overrightarrow{C_{eq}(1)}, \overrightarrow{C_{eq}(2)}, \overrightarrow{C_{eq}(3)}, \overrightarrow{C_{eq}(4)}, \overrightarrow{C_{eq}(ave)}\}$$

(29)

Every particle in every iteration refreshes its concentration with the random choice among up-and-comers picked with a similar likelihood. For example, in the starting iteration, the principal particle refreshes the entirety of its concentrations dependent on $\overrightarrow{C_{eq}(1)}$; at that point, in the subsequent cycle, it might refresh its concentration-dependent on $\overrightarrow{C_{eq(ave)}}$.

5.1.3 Exponential variable term ($F$)

The exponential term ($F$) which can be added to the primary concentration can be defined as:

$$F = e^{-\lambda (t-h)}$$

(30)

where $t$ shows the time, which can be defined as:

$$t = \left(1 - \frac{\text{Iteration}}{\text{Max_iteration}}\right) \left(a_2 \frac{\text{Iteration}}{\text{Max_iteration}}\right)$$

(31)

where Iteration and Max_iteration denote the present and highest limit of the number of iterations, respectively, and $a_2$ is a constant value utilized to oversee the exploitation performance.

To ensure convergence by hindering the search speed alongside improving the exploration and exploitation performance, this investigation likewise considers:

$$t_0 = \frac{1}{A} \ln(-a_1 \text{sign}(r - 0.5)[1 - e^{-\lambda t_0}]) + t$$

(32)

where $a_1$ is a term that regulates exploration in the region of search space, the more the value of $a_1$, the exploration will be more and thusly the lesser exploitation performance. Correspondingly, the more value of the $a_2$, the enhanced exploitation performance and the poor the exploration performance. The term, $\text{sign}(r - 0.5)$, impacts on the heading of exploration performance and exploitation performance. $R$ denoted the random vector in the span of 0 and 1.

The modified version of Equation (30) is represented by Equation (33) which can be obtained by the substitution of Equation (30) into Equation (32):

$$F = a_1 \text{sign}(r - 0.5)[e^{-\lambda t} - 1]$$

(33)

5.1.4 Generation rate ($G$)

The rate of generation is a vital term in the EO algorithm, it gives the proper solution with the enhancement of the exploitation stage by considering the exponential first-order decay process and defined as:

$$G = G_0 e^{-k(t-h)}$$

(34)

In the above Equation (34), $G_0$ indicates the starting value and $k$ denotes the decay constant. To have a progressively controlled and orderly search pattern and to restrict the number of arbitrary factors, this investigation accepts $K = 2$ and utilizes the recently derived exponential term. In this manner, the last arrangement of generation rate conditions is as per the following:

$$G = G_0 e^{-k(t-h)} = G_0 F$$

(35)

where

$$G_0 = GCP(C_{eq} - \overrightarrow{C})$$

(36)

$$GCP = \begin{cases} 0.5r_1 & \text{if } r_2 \geq GP \\ 0 & \text{if } r_2 \leq GP \end{cases}$$

(37)

In the Equation (37), $r_1$ and $r_2$ denote the random numbers in the span $[0, 1]$ and the vector GCP is developed by the repetition of a similar value came about because of Equation (34). At last, the refreshing principle of EO will be as per the following:

$$C = C_{eq} + (C - C_{eq})F + \frac{G}{\lambda V}(1 - F)$$

(38)
In the above equation, $F$ is defined in Equation (33), and $V$ is assumed as unity.

### 5.1.5 Particle’s memory saving

Including memory liberating methods helps every particle in monitoring its directions in the space, which likewise advises its fitness worth. This component looks like the ‘pbest’ idea in PSO. The objective function of every particle in the present iteration is contrasted with that of the past iteration and will be overwritten on the previous if it accomplishes a superior fit. This component helps in exploitation ability yet can expand the opportunity of getting caught in nearby minima if the technique does not assist by global exploration ability.

### 5.1.6 Exploration performance of EO

In brief, there are many terms which influence the process of exploration in EO, these are as follows:

- $a_1$: It regulates the exploration behaviour of the algorithm. It decides that the new position of the particle would be how much away from the particle at the equilibrium. The more the value of $a_1$, the better the exploration rate.
- $\text{Sign}(r-0.5)$: It regulates how exploration should be carried out. The variable $r$ is in the span of $[0, 1]$ with uniform appropriation, there is an equivalent likelihood of negative and positive signs.
- Generation probability (GP): It regulates the cooperation likelihood of concentration up-gradation with the help of the generation rate.
- Equilibrium pool: This vector comprises of five particles. The choice of five particles is to some degree discretionary yet was picked dependent on observational testing.

### 5.1.7 Exploitation performance of EO

The primary parameters to start exploitation are as per the following:

- $a_2$: This parameter has the same role as of $a_1$, but it regulates the exploitation behaviour. It decides the amount of exploitation by burrowing around the best result.
- $\text{Sign}(r - 0.5)$: It regulates how much better exploitation takes place. It determines the way of a nearby hunt.
- Memory saving: Saving memory, spares various best-so-far particles and substitutes them for poor particles.
- Equilibrium pool: When the iteration is going forward, exploration grows dim and exploitation grows in. In this manner, in the last iteration cycle, where the harmony up-and-comers are near one another, the concentration updating procedure will help in neighbourhood search around the up-and-comers, prompting exploitation.

### 5.1.8 Computational complexity of EO

The complexity of computation of an optimization technique is introduced by a capacity relating the running time of the calculation to the info size of the issue. For this reason, the selected parameters are, common terminology as ‘O’, number of particles ‘$n$’, the dimensions ‘$d$’, number of iteration ‘$t$’ and cost function assessment is ‘$r$’.

\[
O(EO) = O(\text{problem definition}) + O(\text{initialization}) + O(t(\text{function evaluations})) + O(t(\text{memory saving})) + O(t(\text{concentration update})) \tag{39}
\]

Hence the total computational complexity can be expressed as:

\[
O(EO) = O(1 + nd + tcn + tn + ind) \approx O(ind + tcn) \tag{40}
\]

As given in Equation (39), it is expressed as the order of a polynomial. Therefore, the EO is an efficient technique. The complexity of EO with that of two standard algorithms PSO and GA is compared in Appendix A-1.

### 5.2 Proposed modified equilibrium optimization algorithm (MEO)

In the main EO method, the four best-so-far particles alongside the average of particles are utilized to build a balanced pool as communicated in Equation (35). The average of particles is likewise determined utilizing the arithmetic average of the four best-so-far particles regardless of their wellness worth. In the recommended MEO technique, a weighted mean methodology is utilized where more significance is given to the fittest particles. In EO, particles move towards the best particles during the search process. In the early stages, the best particle position is not known. Therefore, using large steps initially may result in moving particles far off the optimum position. Therefore, scaling factors are employed to control the movement of particles during the early stages of the algorithm. The original Equation (39) is replaced by Equation (40) as given below:

\[
\overline{C_{\text{eq}(avg)}} = \frac{\overline{C_{\text{eq}(1)}} + \overline{C_{\text{eq}(2)}} + \overline{C_{\text{eq}(3)}} + \overline{C_{\text{eq}(4)}}}{4} \tag{41}
\]

\[
\overline{C_{\text{eq}(avg)}} = SF \ast \frac{4\overline{C_{\text{eq}(1)}} + 3\overline{C_{\text{eq}(2)}} + 2\overline{C_{\text{eq}(3)}} + \overline{C_{\text{eq}(4)}}}{10} \tag{42}
\]
where the scaling factor is varied linearly from an initial value to a final value during an iteration. For the proper selection of scaling factor (SF) different values of SF are assigned and tested in benchmark functions. It is observed that the best results are obtained when SF is varied from 0.01 to 1 during iterations.

6 SIMULATION RESULTS AND DISCUSSION

6.1 Model verification

In the present paper, the performance evaluation of the MEO technique has been performed using some benchmark test functions. This simulation is performed with an Intel (R) core i-5 eighth-generation CPU, of 2.4 GHz, 4 GB RAM PC, with the MATLAB 7.18.0 environment. The proposed algorithm is run multiple times around 500 times alongside the researched system and the best incentive among them is considered as the controller parameters. For all test classifications, EO utilizes 30 particles alongside 500 iterations. Additionally, to give a reasonable correlation, different strategies likewise utilizes 500 runs. The statistical outcomes such as best, worst and mean fitness value are gathered in Table 3 for some unimodal ($f_1$ to $f_7$) and multimodal ($f_8$ to $f_{10}$) functions. From the table is seen that out of 10 functions except for $f_5$ and $f_9$ all the other function provides better results compared to EO and some standard algorithms. Figure 3(A–D) indicates the convergence characteristic curve for all the standard benchmark functions ($f_1$ to $f_4$) considered for the study by considering the EO and MEO algorithm.

It tends to be seen that the exhibition of the proposed modified algorithm is a lot of prevalent than the standard algorithm. To validate the superiority of the MEO technique, EO and some published whale optimization (WOA) and modified WOA [29] results are also given in Table 3. It is evident from table that, for most of the test functions, the proposed MEO technique is very efficient when contrasted with a different algorithm. In this way, the proposed modified approach can be utilized to figure the IT2FPID controller parameters for the hybrid power system.

Table 4 also shows the computational time for 30 runs for all the benchmark functions for MEO and EO algorithms. It can be observed from Table 4 that, for all the functions ($f_1$–$f_{10}$) computational times are less for the proposed MEO algorithm compared to the original EO algorithm. This is due to the introduction of the scaling factor which reduces the simulation time and fitness function. Thus, the above study proves that the proposed approach better results thus can be used for further study.

6.2 Implementation of proposed modified EO algorithm

An unsettling disturbance is thought of for the proposed system through which the objective function can be computed and the simulation is carried out. Here, Equation (21) is utilized to discover the parameters of the IT2FPID and PID controller. For a comparison point of view, all the optimized controller parameters are given in Table 5. It can be seen that when the modified technique is employed to tune the IT2FPID controller, the objective function becomes 0.1316 compared to 0.3178 of
TABLE 3 Comparison of fitness function values for the proposed MEO algorithm for some standard benchmark functions ($f_1$–$f_{10}$)

| Function | DE [41] | PSO [41] | GSA [5] | hGGSA-PS [5] | WOA [32] | MWOA [32] | EO | Proposed MEO |
|----------|---------|---------|--------|-------------|---------|----------|----|-------------|
| Avg. | Std. Dev. | Avg. | Std. Dev. | Avg. | Std. Dev. | Best | Mean | Best | Mean | Best | Mean | Best | Mean | Best | Mean |
| $f_1$ | $1.5 \times 10^{-9}$ | $3.56 \times 10^{-10}$ | $5.9 \times 10^{-14}$ | $0.934 \times 10^{-24}$ | $6.40 \times 10^{-29}$ | $0.930 \times 10^{-24}$ | $0.930 \times 10^{-24}$ |
| $f_2$ | $1.5 \times 10^{-9}$ | $3.56 \times 10^{-10}$ | $5.9 \times 10^{-14}$ | $0.934 \times 10^{-24}$ | $6.40 \times 10^{-29}$ | $0.930 \times 10^{-24}$ | $0.930 \times 10^{-24}$ |
| $f_3$ | $1.5 \times 10^{-9}$ | $3.56 \times 10^{-10}$ | $5.9 \times 10^{-14}$ | $0.934 \times 10^{-24}$ | $6.40 \times 10^{-29}$ | $0.930 \times 10^{-24}$ | $0.930 \times 10^{-24}$ |
| $f_4$ | $1.5 \times 10^{-9}$ | $3.56 \times 10^{-10}$ | $5.9 \times 10^{-14}$ | $0.934 \times 10^{-24}$ | $6.40 \times 10^{-29}$ | $0.930 \times 10^{-24}$ | $0.930 \times 10^{-24}$ |
| $f_5$ | $1.5 \times 10^{-9}$ | $3.56 \times 10^{-10}$ | $5.9 \times 10^{-14}$ | $0.934 \times 10^{-24}$ | $6.40 \times 10^{-29}$ | $0.930 \times 10^{-24}$ | $0.930 \times 10^{-24}$ |
| $f_6$ | $1.5 \times 10^{-9}$ | $3.56 \times 10^{-10}$ | $5.9 \times 10^{-14}$ | $0.934 \times 10^{-24}$ | $6.40 \times 10^{-29}$ | $0.930 \times 10^{-24}$ | $0.930 \times 24$ |
| $f_7$ | $1.5 \times 10^{-9}$ | $3.56 \times 10^{-10}$ | $5.9 \times 10^{-14}$ | $0.934 \times 10^{-24}$ | $6.40 \times 10^{-29}$ | $0.930 \times 24$ | $0.930 \times 24$ |
| $f_8$ | $1.5 \times 10^{-9}$ | $3.56 \times 10^{-10}$ | $5.9 \times 10^{-14}$ | $0.934 \times 10^{-24}$ | $6.40 \times 10^{-29}$ | $0.930 \times 24$ | $0.930 \times 24$ |
| $f_9$ | $1.5 \times 10^{-9}$ | $3.56 \times 10^{-10}$ | $5.9 \times 10^{-14}$ | $0.934 \times 10^{-24}$ | $6.40 \times 10^{-29}$ | $0.930 \times 24$ | $0.930 \times 24$ |
| $f_{10}$ | $1.5 \times 10^{-9}$ | $3.56 \times 10^{-10}$ | $5.9 \times 10^{-14}$ | $0.934 \times 10^{-24}$ | $6.40 \times 10^{-29}$ | $0.930 \times 24$ | $0.930 \times 24$ |

MEO-based T1FPID type and 0.4855 of MEO-based PID controller. Finally, it is observed that the percentage improvement in $J$ value with the proposed MEO-based IT2FPID controller compared to MEO-based T1FPID and PID are 81.20% and 54.63% respectively.

Hence, it can be concluded that for the engineering design problem also proposed MEO technique provides better results compared to the original EO technique. To assess the time-domain performance, the accompanying scenario is thought of.

### 6.3 Scenario-1: Step change of 1% in Area-1

The dynamic execution of the hybrid system is estimated by applying a 1% step load in zone 1. Figure 4(A–C) shows the response of the hybrid system in terms of area-1, area-2 and tie-line power variation with the proposed controllers for the above disturbance. A conclusion can be made that the proposed MEO-based IT2FPID controller provides better results as compared to others like MEO-based T1FPID and the conventional PID controller.

### 6.4 Scenario-2: Step change of a 1% in area-1 and 2% in area-2

In this scenario, the hybrid power system is verified by considering another disturbance as 1% step load change in area-1 as well as 2% in area-2. The response of the system with the scenario-2 is shown in Figure 5(A–C). From the simulation results, it is discovered that if there should arise an occurrence of a modified EO based T2FPID controller, arrived at a consistent state of equilibrium when contrasted with MEO-based T1FPID, MEO-based T1FPID and EO-based PID controller.

### 6.5 Scenario-3: Realisation of the hybrid system using non-linearities like GRC, TD, and GDB

In this scenario, the hybrid power system is verified by considering non-linearities like governor rate constant (GRC), governor dead band (GDB) and turbine dynamics (TD). The controller parameters for the above case are shown in Table 6. The response of the system with the scenario-3 is shown in Figure 6(A,B). From the simulation results, it is discovered that the proposed modified EO based T2FPID controller provides best result as compared to MEO-based T1FPID, MEO and EO-based PID controller by adding different non-linearity like GRC, TD, and GDB.

### 6.6 Scenario-4: Sensitivity analysis

The sensitivity is performed by considering the varying solar input power and wind input power as appeared in Figure 7(A,B).
### TABLE 4 Comparison of computational time between MEO and EO algorithms for $f_1$–$f_{10}$

| Function | % Reduction in execution time | Proposed MEO Elapsed time (s) | EO Elapsed time (s) |
|----------|-------------------------------|-------------------------------|---------------------|
| $f_1$    | 20.191                        | 10.676                        | 13.377              |
| $f_2$    | 8.651                         | 13.715                        | 15.014              |
| $f_3$    | 5.498                         | 40.269                        | 42.612              |
| $f_4$    | 19.951                        | 12.663                        | 15.819              |
| $f_5$    | 22.969                        | 14.789                        | 19.199              |
| $f_6$    | 16.389                        | 10.509                        | 12.569              |
| $f_7$    | 6.744                         | 17.321                        | 18.564              |
| $f_8$    | 12.791                        | 15.476                        | 17.745              |
| $f_9$    | 11.174                        | 10.620                        | 11.956              |
| $f_{10}$ | 34.452                        | 11.385                        | 17.369              |

respectively. Figure 8(A,B) shows the time response of the hybrid system by considering scenario-4. The same conclusion can be drawn that the proposed MEO-based T2FPID controller gives the best results compared to other standard approaches.

### 6.7 Scenario-4: Realization of said power system by considering a different objective function

At long last, the amleness of the sketched-out controllers is confirmed through various lists of performance indices. For instance:

The integral of squared error (ISE)

$$ISE = \int_0^{t_{sim}} (|\Delta F_1| + |\Delta F_2| + |\Delta P_{ref}|) \cdot dt$$  (40)

Table 5 gives the assessments of various performance indices of each controller. It is clear from the tables that the ITAE objective function provides fewer errors as compared to other indices.

### 7 CONCLUSION

In this paper, a novel methodology is made by proposing a modified equilibrium optimization algorithm (MEO) for an interval type-2 fuzzy PID controller structure for frequency regulation of a hybrid power system. The prevalence of the modified algorithm over EO and some conventional algorithms as far as simulation time and fitness function is looked at by taking a few benchmark functions. As an after stage, the proposed MEO technique is then applied to improve IT2FPID controller parameters for the frequency response of the hybrid power system. It is observed that the percentage improvement in $J$ value with the proposed MEO technique under normal operation, the percentage improvement in $J$ value with the proposed IT2FPID controller compared to MEO-based T1FPID and PID are 81.20% and 54.63% respectively. It is also seen that the MEO-based IT2FPID controller is logically fruitful in terms of overshoots, undershoots, simulation time and integral

### TABLE 5 Controller parameters for the hybrid distributed power system

| Parameter | Proposed MEO-based interval type-2 fuzzy PID controller | MEO-tuned type-1 fuzzy PID controller | MEO-tuned PID | EO-tuned PID |
|-----------|---------------------------------------------------------|---------------------------------------|---------------|--------------|
| $K_{P1}$  | -1.5098                                                 | 1.9959                                | 1.9916        | 1.9986       |
| $K_{I1}$  | 1.9986                                                  | 1.9989                                | 1.1338        | 0.5370       |
| $K_{D1}$  | -0.6613                                                 | -1.9984                               | 1.9986        | 0.5827       |
| $K_{P2}$  | 0.9252                                                  | 1.0011                                | —             | —            |
| $K_{I2}$  | 0.2788                                                  | 0.4203                                | —             | —            |
| $K_{D2}$  | -1.9805                                                 | -1.6769                               | 0.2978        | -0.3177      |
| $K_{p1}$  | -1.9805                                                 | -1.9987                               | 0.2176        | 1.3634       |
| $K_{t1}$  | 0.9865                                                  | 1.9985                                | 0.6102        | -0.4521      |
| $K_{t2}$  | 0.0905                                                  | 0.0265                                | —             | —            |
| $K_{t2}$  | 0.9998                                                  | 0.2828                                | —             | —            |
| ITAE      | 0.1316                                                  | 0.3178                                | 0.4855        | 0.7006       |
FIGURE 4  Response of the hybrid power system for Scenario-1. (A) Frequency response curve for area-1. (B) Frequency response curve for area-2. (C) Curve for tie-line power.
FIGURE 5  Response of hybrid power system for Scenario-2. (A) Frequency response curve for area-1. (B) Frequency response curve for area-2. (C) Curve for tie-line power.
FIGURE 6  Response of the system for Scenario-3. (A) Frequency response curve for area-1. (B) Frequency response curve for area-2

FIGURE 7  Random loading pattern for area-1 and area-2. (A) Loading pattern in area-1. (B) Loading pattern in area-2
**FIGURE 8** Response of the system for Scenario-4. (A) Frequency response curve for area-1. (B) Frequency response curve for area-2

**TABLE 6** Controller parameters for the hybrid distributed power system considering non-linearity

| Parameter | Proposed MEO-based interval type-2 fuzzy PID controller | MEO-tuned type-1 fuzzy PID controller | MEO-tuned PID | EO-tuned PID |
|-----------|---------------------------------------------------------|--------------------------------------|---------------|--------------|
| $K_{P1}$  | 0.8767                                                  | 1.5107                               | $-1.0755$     | $-1.8400$    |
| $K_{I1}$  | 0.6200                                                  | $-0.5166$                            | 0.1007        | $-1.0382$    |
| $K_{D1}$  | 0.3148                                                  | 0.2485                               | $-0.3968$     | $-1.6395$    |
| $K_{P2}$  | 1.3296                                                  | 1.5282                               |               |              |
| $K_{I2}$  | 0.7359                                                  | 0.9041                               |               |              |
| $K_{D2}$  | 1.2002                                                  | 0.8556                               | $-1.9898$     | $-1.9898$    |
| $K_{11}$  | 1.4953                                                  | 1.7646                               | $-1.0221$     | $-0.8395$    |
| $K_{22}$  | 0.6602                                                  | 0.0525                               | $-1.9865$     | $-1.4354$    |
| $K_{11}$  | 1.9185                                                  | 1.5087                               |               |              |
| $K_{22}$  | 0.5042                                                  | 0.1191                               |               |              |
| ITAE      | 0.0084                                                  | 0.0481                               | 0.1347        | 0.2020       |
TABLE 7  Optimized lead-lag controller parameters for different objective functions

| Techniques/controller/ objective function | ITAE | ISE | IAE | ITSE |
|-------------------------------------------|------|-----|-----|------|
| Proposed MEO-tuned Typ-2 Fuzzy PID controller | 0.1316 | 0.3141 | 2.853 | 6.183 |
| MEO-tuned type-1 fuzzy PID controller | 0.3178 | 1.827 | 6.769 | 36.36 |
| MEO-tuned PID | 0.4855 | 3.918 | 9.796 | 80.13 |
| EO-tuned PID | 0.7006 | 7.53 | 13.59 | 152.5 |

errors of for frequency control issues that appeared differently concerning conventional controller design by EO algorithm by taking some genuine circumstance of the hybrid power system.

NOMENCLATURE

| AGC | Automatic generation control |
| BESS | Battery energy storage system |
| DEG | Diesel engine generator |
| DG | Distributed energy sources |
| FC | Fuel cell |
| FLC | Fuzzy logic controller |
| HAE | Hydro-aqua electrolyser |
| IT2FPID | Interval type-2 fuzzy PID controller |
| $K_{WTG}$, $T_{WTG}$ | Gain and time constant of wind turbine |
| $K_{HAE}$, $T_{HAE}$ | Gain and time constant of hydro-aqua electrolyser |
| $K_{FC}$, $T_{FC}$ | Gain and time constant of hydro-aqua electrolyser |
| $K_{FESS}$, $T_{FESS}$ | Gain and time constant of flywheel energy storage |
| $K_{DEG}$, $T_{DEG}$ | Gain and time constant of diesel engine generator |
| $K_{MTG}$, $T_{MTG}$ | Gain and time constant of microturbine |
| $K_p$, $T_p$ | Gain and time constant of power system |
| LFC | Load frequency control |
| LMF | Lower membership function |
| MTG | Micro-turbine |
| RES | Renewable energy source |
| T1FPID | Type-1 fuzzy PID controller |
| UMF | Upper membership function |
| WTG | Wind turbine generator |
| $\Delta f$ | Frequency deviation |

REFERENCES

1. Elgerd, O.I.: Electric Energy Systems Theory. Tata McGraw Hill, New Delhi (2006)
2. Tian, E., Peng, C.: Memory-based event-triggering H∞ load frequency control for power systems under deception attacks. IEEE Trans. Cybern. 50, 4610–4618, (2020)
3. Fatih, A., Kassem, A.M.: Antlion optimizer-ANFIS load frequency control for multi-interconnected plants comprising photovoltaic and wind turbine. ISA Trans. 1(87), 282–296 (2018)
4. Hasan, N.: Design and analysis of pole-placement controller for interconnected power systems. Int. J. Emerg. Technol. Adv. Eng. 2(8), 212–217 (2012)
5. Khadanga, R.K., Kumar, A.: Hybrid adaptive ‘gbest’-guided gravitational search and pattern search algorithm for automatic generation control of multi-area power system.' IET Gener. Transm. Distrib. 11(13), 3257–3267 (2016)
6. Sahu, B.K., Mohanty, P.K.: Design and implementation of Fuzzy-PID controller with derivative filter for AGC of two-area interconnected hybrid power system. Int. J. Innovative Technol. Explor. Eng. 8, 4198–4212 (2019)
7. Ahmadreza, A., Monsef, H., Wu, B.: Load frequency control by de-loaded wind farm using the optimal fuzzy-based PID droop controller. IET Renewable Power Gener. 13(1), 180–190 (2018)
8. Hasanien, H.M., El-Fergany, A.A.: Salp swarm algorithm-based optimal load frequency control of hybrid renewable power systems with communication delay and excitation cross-coupling effect. Electr. Power Syst. Res. 176, 105938 (2019)
9. Zargar, M.Y., Mufti, M.U.D., Lone, S.A.: Adaptive predictive control of a small capacity SMES unit for improved frequency control of a wind-diesel power system. IET Renewable Power Gener. 11(14), 1832–1840 (2017)
10. Kumar, A., Shankar, G.: Optimal load frequency control in de-loaded tidal power generation plant-based interconnected hybrid power system. IET Renewable Power Gener. 12(16), 1864–1875 (2018)
11. Chown, G.A., Hartman, R.C.: Design and experience with a fuzzy logic controller for automatic generation control (AGC). IEEE Trans. Power Syst. 13(13), 965–970 (1998)
12. Sahu, R.K., Panda, S., Sekhar. G.T.C.: A novel hybrid PSO-PS optimized fuzzy PI controller for AGC in multi area interconnected power systems. Int. J. Electr. Power Energy Syst. 64, 880–893 (2015)
13. Arya, Y.: Improvement in automatic generation control of two-area electric power systems via a fuzzy aided optimal PID- FOI controller. ISA Trans. 80, 475–490 (2018)
14. Arya, Y., Kumar: BFOA-scaled fractional order fuzzy PID controller applied to AGC of multi-area multi-source electric power generating systems. Swarm Evol. Comput. 32, 202–218 (2017)
15. Dokht, S.A., et al.: Online adaptive type-2 fuzzy logic control for load frequency of multi-area power system. J. Intell. Fuzzy Syst. 37(1), 1033–1042 (2019)
16. Bevrani, H., Feizi, M.R., Atae, S.: Robust frequency control in an islanded microgrid: H∞-synthesis approaches. IEEE Trans. Smart Grid 7(2), 706–717 (2016)
17. Ali, E.S., Abd-Elazim, S.M.: BFOA based design of PID controller for two area load frequency control with nonlinearities. Int. J. Electr. Power Energy Syst. 51, 224–231 (2015)
18. Hassan, K.M., Niknam, T.: A new intelligent online fuzzy tuning approach for multi-area load frequency control Self-Adaptive Modified Bat Algorithm. Int. J. Electr. Power Energy Syst. 71, 254–261 (2015)
19. Zhang, Z., et al.: An adaptive particle swarm optimization algorithm for reservoir operation optimization. Appl. Soft Comput. 18, 167–177 (2014)
20. Fatemeh, D., Bevrani, H.: Multiobjective design of load frequency control using genetic algorithms. Int. J. Electr. Power Energy Syst. 42(1), 257–263 (2012)
21. Almoataz, A.Y., Ali, E.S.: Load frequency controller design via artificial cuckoo search algorithm. Electr. Power Compon. Syst. 44(1), 90–98 (2016)
22. Sekhar, G.C., et al.: Load frequency control of power system under deregulated environment using optimal firefly algorithm. Int. J. Electr. Power Energy Syst. 74, 195–211 (2016)
23. Sahu, R.K., Panda, S., Pradhan, S.: Optimal gravitational search algorithm for automatic generation control of interconnected power systems. Ain Shams Eng. J. 5(3), 721–733 (2014)
24. Wang, Y., et al.: A hierarchical gravitational search algorithm with an effective gravitational constant. Swarm Evol. Comput. 46, 118–139 (2019)

25. Latif, A., et al.: Comparative performance evaluation of WCA-optimised non-integer controller employed with WPG–DSPG–PHEV based isolated two-area interconnected microgrid system. IET Renewable Power Gener. 13, 725–736 (2019)

26. Latif, A., et al.: Maiden coordinated load frequency control strategy for ST-AWEC-GECDG-based independent three-area interconnected microgrid system with the combined effect of diverse energy storage and DC link using BOA-optimised PFOID controller. IET Renewable Power Gener. 13, 2634–2646 (2019)

27. Faramarzi, A., et al.: Equilibrium optimizer: A novel optimization algorithm. Knowledge-Based Syst. 191, 105–190 (2020)

28. Zhou, B., et al.: Equilibrium-inspired multiple group search optimization with synergistic learning for multi-objective electric power system dispatch. IEEE Trans. Power Syst. 28(4), 3534–3545 (2013)

29. Zhang, X., et al.: Equilibrium-inspired multiagent optimizer with extreme transfer learning for decentralized optimal carbon-energy combined-flow of large-scale power systems. Appl. Energy 189, 157–176 (2017)

30. Lee, D.J., Wang, L.: Small-signal stability analysis of an autonomous hybrid renewable energy power generation/energy storage system part I: Time-domain simulations. IEEE Trans. Energy Convers. 23, 311–320 (2008)

31. Singh, K., et al.: An integral tilt derivative control strategy for frequency control in multi-microgrid system. IEEE Syst. J. 15(1), 1477–1488 (2020)

32. Khadanga, R.K., Kumar, A., Panda, S.: A novel modified whale optimisation algorithm for load frequency controller design of a two-area power system comprising of PV grid and thermal generator. Neural Comput. Appl. 13, 1–12 (2019)

33. Hosseinzadeh, M., Salmasi, F.R.: Power management of an isolated hybrid AC/DC micro-grid with fuzzy control of battery banks. IET Renewable Power Gener. 9, 484–493 (2015)

34. Çam, E., Kocaarslan, I.: Load frequency control in two area power systems using fuzzy logic controller. Energy Convers. Manage. 46, 233–243 (2005)

35. Pan, I., Das, S.: Fractional order AGC for distributed energy resources using robust optimization. IEEE Trans. Smart Grid 7, 2175–2186 (2015)

36. Das, D.C., Roy, A.K., Sinha, N.: GA-based frequency controller for solar thermal–diesel–wind hybrid energy generation/energy storage system. Int. J. Electr. Power Energy Syst. 43, 262–279 (2012)

37. Sinha, A., Jana, K.C.: Comprehensive review on control strategies of parallel-interfaced voltage source inverters for distributed power generation system. IET Renewable Power Gener. 14(13), 2297–2314 (2020)

38. Yang, J., et al.: LSTM auto-encoder based representative scenario generation method for hybrid hydro–PV power system. IET Gener. Transm. Distrib. 14(24), 5935–5943 (2020)

39. Abuelenin, S.M., Abdel-Kaue, R.F.: Closed-form mathematical representations of interval type-2 fuzzy logic systems. arXiv preprint arXiv:1706.05593 (2017)

40. Castillo, O., et al.: A comparative study of type-1 fuzzy logic systems, interval type-2 fuzzy logic systems and generalized type-2 fuzzy logic systems in control problems. Inf. Sci. 354, 257–274 (2016)

41. Sahu, P.R., Hota, P.K., Panda, S.: Modified whale optimization algorithm for fractional-order multi-input SSSC-based controller design. Optim. Control Appl. Methods 39, 1802–1817 (2018)

42. Sahu, R.K., Gorripotu, T.S., Panda, S.: Automatic generation control of multi-area power systems with diverse energy sources using teaching learning-based optimization algorithm. Eng. Sci. Technol. Int. J. 19, 113–134 (2016)

How to cite this article: Kumar Khadanga, R., Kumar, A., Panda, S.: Frequency control in hybrid distributed power systems via type-2 fuzzy PID controller. IET Renew Power Gener. 15, 1706–1723 (2021). https://doi.org/10.1049/rpg2.12140

APPENDIX A

A1. Standard benchmark functions description

A2. Complexity calculation

Let ‘t’ represents dimensions, ‘i’ shows the iteration, ‘n’ shows the population, ‘m’ shows total number of off springs with ‘α’ shows a percentage value of sum of mutated population and off springs to the populations.

PSO complexity:

\[ O(PSO) = O(problem\ de\ finition) + O(initialization) + O(t(\ function\ evaluations)) + O(t(memory\ saving)) + O(t(concentration\ update)) \]

\[ O(PSO) = n + O(t) + O(tcn) + O(tnd) \]

\[ O(PSO) = O(tcn + tnd) \]

GA complexity:

\[ O(GA) = O(problem\ de\ finition) + O(initialization) + O(T(function\ evaluations)) + O(T(roletshell) + O(T(crossover)) + O(T(mutuation)) \]

\[ c + m is equal to αn; T = t / a. \] Using this equation, the updated GA complexity equation is:

\[ O(GA) = n + O(tnd) + O(Td) + O(c) + O(Td) + O(Tmpd) \]

\[ O(GA) \cong O(Tmpd + cd + Ten) \]

We consider \( α = 1 \). Thus \( T = t \) and \( c + m = n \)

\[ O(GA) = O(t(c + m)d + Ten) = O(tnd + ten) \]
| Types          | Function                                      | Dim. | Range            | $f_{\text{min}}$ |
|---------------|-----------------------------------------------|------|------------------|-----------------|
| Uni-modal     | $f_1(x) = \sum_{i=1}^{n} x_i^2$               | 30   | $[-100,100]$     | 0               |
|               | $f_2(x) = \sum_{i=1}^{n} |x_i| + \prod_{i=1}^{n} |x_i|$          | 30   | $[-10,10]$       | 0               |
|               | $f_3(x) = \sum_{i=1}^{n} (\sum_{j=1}^{i} x_j)^3$ | 30   | $[-100,100]$     | 0               |
|               | $f_4(x) = \max_i(|x_i|, 1 \leq i \leq n)$    | 30   | $[-100,100]$     | 0               |
|               | $f_5(x) = \sum_{i=1}^{n} (100(x_{i+1} - x_i^2)^2 + 1)$ | 30   | $[-30,30]$       | 0               |
|               | $f_6(x) = \sum_{i=1}^{n} (|x_i| + 0.5)^2$     | 30   | $[-100,100]$     | 0               |
|               | $f_7(x) = \sum_{i=1}^{n} e^{0.5 x_i^2}$       | 30   | $[-1.28,1.28]$   | 0               |
| Multi-modal   | $f_8(x) = \sum_{i=1}^{n} -x_i \sin(\sqrt{|x_i|})$ | 30   | $[-500,500]$     | $-418.9829 \times n$ |
|               | $f_9(x) = \sum_{i=1}^{n} -x_i^2 - 10 \cos(2\pi x_i) + 10$ | 30   | $[-5.12,5.12]$   | 0               |
|               | $f_{10}(x) = -20 \exp(-0.2 \sqrt{\sum_{i=1}^{n} x_i^2}) - \exp\left(\frac{\sum_{i=1}^{n} \cos(2\pi x_i)}{n}\right) + 20 + e$ | 30   | $[-600,600]$     | 0               |