Secondary Control of Islanded Microgrids Using PI-Evolutionary Algorithms Under Uncertainties

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Abstract- Electrical grids converge now to a novel concept which named Microgrids (MG). it consists on producing energy in order to reduce dependency on fuel known by its fluctuant cost and to decrease harmful emission in the atmosphere. Constituted by renewable sources, energy storage system and controllable sources, a hybrid combination of these DERs is adopted to maintain MG reliability, transparency and efficiency of the whole system under deregulated power production. MG always are influenced by random weather conditions (e.g. temperature, solar radiation, wind speed. . .) of the non-controllable sources and load. These perturbations affect quality of energy especially frequency as a sensitive parameter to active power balance. To deal with this issue, a smart management of controllable sources is highly recommended to minimize frequency deviation. In this paper, a dynamic model is adopted with PI controller in controllable sources and storage system and presents a novel approach to design PI controller parameters by hybrid Evolutionary Algorithm (EA) GA-TLBO as a robust control of frequency regulation under uncertainty. A simulated isolated MG is tested on scenarios to validate the approach adopted in conceiving the PI parameters to avoid the frequency fluctuation in the different cases of study.

Keywords Isolated MG; controlled sources; noncontrolled sources; frequency control; PI controller; evolutionary algorithm; genetic algorithm; teaching-learning based optimization.

Nomenclature:

BBO	:Biogeography-Based Optimization
DE	:Differential evolution
DEG	:Diesel generator
DER	:Distributed energy resource
DG	:Distributed generator
DGA	:Differential genetic algorithm
EA	:Evolutionary algorithm
ESS	:Energy storage system
FA	:Firefly Algorithm
FC	:Fuel cell
GA	:Genetic algorithm
hDE	:hybrid Differential Evolution
HS	:Harmony search
HIS	:High Suitability Index
ISE	:Integral square error
IAE	:Integral Absolute Error
LFC	:Load frequency control
MID	:Modified Integral Derivative
MOBHA	:Modified black hole optimization algorithm
MOEO	:Multi-objective extremal optimization fractional order PID
MOFOFPID	:Multi-objective Fuzzy-Order-Fractional proportional integral derivative
MOFPI	:Multi-objective fractional proportional integral
MOPI	:Multi-objective proportional integral
MT	:Micro turbine

PI	:Proportional Integral
PSO	:Particle swarm optimization
PV	:Photovoltaic panel
QOHSA	:Quasi-oppositional harmony search algorithm
SA	:Simulated annealing
TLBO	:Teaching Learning-Based Optimization
WT	:Wind turbine

1. Introduction

Microgrids are considered now as innovative idea to deal with economic and ecological problems of classical grids. These entities are implanted in autonomous mode in rural and far areas from the main grid. So, it's a perfect solution to prevent expensive cost of electrical installation and connection losses. Despite of intermittence of renewable sources as non-controlled sources, MG are known by their transparency, flexibility and intelligence ensured by the implementation of ESS and controllable sources like DEG, FC also MT. Adopting an autonomous MG, LFC becomes one of the major challenges dealing with low inertia, time varying delays, parametric uncertainties and fluctuant renewable source and load power. The main idea of this paper is to solve this problem referring to a novel robust approach. In fact, LFC is conceived by a hierarchical strategy [1] based on three dissociated parts or layers: a primary [2] and secondary and tertiary control. This partition depends on duration of frequency perturbation. This matter was discussed also with interconnected classical girds based on synchronous and induction generators [3-4] and more debated with MG.

Several robust control methods are applied to minimize frequency fluctuation on an islanded MG. For example, Bervani in [5,6] compares between H∞ , μ-synthesis robust control techniques to balance load and power under uncertainties, based on linearized MG state-and confirms robustness of μ-synthesis approach. PI controller can be tuned efficiently by several strategies, despite of empiric Ziegler-Nichols method or adopting fuzzy logic approach [7]. As application of MG in shipboards, Khooban in [8] presents a new adaptive and time-varying controller using MOBHA as stochastic multi-objective optimization algorithm for tuning controller parameters in the presence DERs and load disturbances without considering communication delays. In reference [9], an adaptive multi-objective algorithm MOBHA in MOFOFPID to tune the non-integer fuzzy PID controller coefficients. Other authors in [10-11] study another application of MG adopting the same MOBHA with time-delay to improve the performance of the LFC with low computation burden and complexity.

As other approaches, authors of [12-23] tune their controllers using EA. For example, in [12], SA optimization strategy was used to approximate sensitivity of the stability performance of secondary cooperative control to adding/removing data communication links. Reference [13] compares the well-tuned controller with intelligent fuzzy and particle swarm optimization-fuzzy controllers.

The designed controllers are examined under different step, random, and noise disturbances depending on analysis and the ISE indexes. In [14], authors deal with the conception of a robust controller based on a new hybrid DGA-PSO algorithm to enhance the system oscillation damping under various disturbances with different loading conditions by studying the impact of the fractional parameter for an optimal dynamic performance of the system over various perturbed conditions by the low IAE and FD indices. Regarding PI controller the authors in [15] designed a multiple PI controllers parameter in cascade control loop using HSA implemented in a complex and nonlinear system as an efficient comparing with GA and Generalized Reduced Gradient methods. A novel QOHSA was proposed in [16] to obtain the best solution vectors and faster convergence rate by simulating the problem in a dynamic model of MG. In [17,18], TLBO was used to tune the parameters of fuzzy and sliding mode controllers to enhance power stability of the studied system. In [19], the proposed FA optimized PID controller was tested with changing the number of iterations of each algorithm FF algorithm tuned PID controller gained superiority compared to using the GA-PI and PSO-PI tuned controller performance by increasing iteration numbers. The objective function to minimize is ITAE of frequency. Wang in [20] was proposed an effective fractional order frequency PID controller by using a multi-objective extremal optimization algorithm. the proposed MOEO-FOPID can be considered as a competitive multi-objective optimization method for the fractional order frequency control of an islanded microgrid from the perspective of the complexity of algorithm design and computational efficiency. Sahu in [21] demonstrates the effectiveness of hDE-PS optimized MID controller to regulate frequency in a multi-area multi-source power system with perturbed renewable source and load profiles over GA and DE technics. Then authors of [22] compare also between fractional order and integer order controllers to highlight the advantages and disadvantages of type of controller under uncertainty tuned by PSO with unreliable communication network with stochastic delay. BBO was implemented by Rahman in [23] in some specific controllers and presents best results in an interconnected two-area power system. This paper makes in evidence the accuracy of a novel approach for LCF based on hybrid EA under uncertainties as extension of the conference paper [24]. The study in [25] presents a control strategy for the frequency regulation in a MG The proposed method enhances MG reliability, diesel generator efficiency, reducing polluting and optimizing the engine life span. Others control strategy can be adopted in frequency regulation as mentioned in [26] using the droop control method in the primary control and a frequency restoration function in the secondary control with a single and constant time delay. Rezaei in [27] proposes a robust energy and frequency management in islanded MG considering a static modelling of system frequency under uncertainty handling strategy without relying on probability distribution functions. A double sliding mode controller is adopted in the same studied MG to achieve flexible output power control [28]. Application of consensus theory for frequency restoration in secondary control was the main idea of [29] in islanded MG by respecting communication parameters and designing the consensus controller gains taking care of the network communication state. Authors can also take into consideration uncertainties as presented in [30] and predicted error of renewable fluctuant sources [31]. This paper starts by presenting the dynamic model of the studied MG and EAs adopted to tune PI controller parameters in section 2. Section 3 illustrates the problem of our work, and section 4 presents a state of art d some classical evolutionary algorithms. Simulation results to introduce the proposed method and demonstrate its efficiency constitutes section 5, then conclusion as section 6.

2. Modeling of the studied MG

2.1. Dynamic model of MG

The main study in this paper focuses on secondary frequency regulation of autonomous MG by adopting a dynamic model presented in Fig 1. The architecture contains a common AC bus connected to each DRs via electronics devises (inverter for DC DER such as PV, FC and ESS and rectifier inverter in cascade for AC DER specially DEG, MT and WT). Maintaining frequency depends on balancing between production and load as illustrated in Eq. (1).

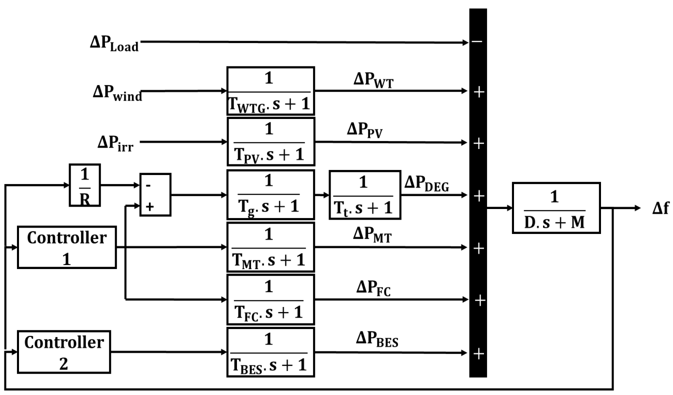

Fig 1. MG dynamical frequency response model

$$P_{Load} = P_{PV} + P_{WT} + P_{DEG} + P_{MT} + P_{FC} + P_{BES} \quad (1)$$

Where: P_{PV} is PV output power, P_{WT} is WT output power, P_{DEG} is DEG output power, P_{MT} is MT output power PFC is FC output power, P_{BES} is BES output power and P_{Load} is the load power. P_{BES} is positive in discharging mode and negative in charging mode.

As already said in the previous paragraphs, PV, WT and load are considered as perturbation in the MG system to provide frequency fluctuation. To compensate this unbalanced power, a control of MT, DEG, and FC is applied named secondary frequency control. In the dynamic model of the studied MG, each DER represented by a simple low-order linearized model to express the change of output power of the DER. The followed equation is obtained to present changes in DRs of MG:

$$\Delta P_{Load} = \Delta P_{PV} + \Delta P_{WT} + \Delta P_{DEG} + \Delta P_{MT} + \Delta P_{FC} + \Delta P_{BES} \quad (2)$$

Referring to the dynamic model, equations of the MG dynamic frequency response model are introduced in the followed Eq. (3-8) and MG parameters are shown in the two tables Table. 1-2:

Table 1. MG rated power

Rated power (kW)		Rated power (kW)	
PV	5	BES	10
WT	5	DEG	20
FC	10	Load	60
MT	10		

Table 2. Parameters of the studied MG

Parameter	Value	Parameter	Value
D (pu/Hz)	0.015	T_{FC} (s)	4
M (pu)	0.1667	T_{MT} (s)	2
T_{PV} (s)	1,8	T_t (s)	0,4
T_{WT} (s)	1,5	T_g (s)	0,08
T_{BES} (s)	0,1		

2.2. Renewable resources

Renewable resources are known also as non-controlled sources. In fact, the electrical PV power is generated from solar radiation power and the output power change ΔP_{PV} is expressed in Eq. (3). WT converts kinetic power of wind to electrical power expressed in Eq. (4).

$$\Delta P_{PV} = \Delta P_{irr}.G_{PV} = \Delta P_{irr}.\frac{1}{1+T_{PV}.s} \quad (3)$$

$$\Delta P_{WT} = \Delta P_{wind}.G_{WT} = \Delta P_{wind}.\frac{1}{1+T_{WT}.s} \quad (4)$$

2.3. Controlled resources:

MT is a small DER which converts hydraulic power to electrical power and the power change ΔP_{MT} is defined in the Eq. (5). FC is a cell that concerts a chemical energy from electrochemical reaction of Hydrogen fuel with oxygen to extract DC electrical power illustrated in Eq. (6). As one of the classical DR, DG is a controlled resource which combine an electrical motor and governor (engine). The control of this DR is made in the governor and its power change can be presented in Eq. (7).

$$\Delta P_{MT} = U.G_{MT} = U.\frac{1}{1+T_{MT}.s} \quad (5)$$

$$\Delta P_{FC} = U.G_{FC} = U.\frac{1}{1+T_{FC}.s} \quad (6)$$

$$\Delta P_{DEG} = U.G_{DEG} = U\frac{1}{(1+T_t.s).(1+T_g.s)} \quad (7)$$

2.4. Energy storage system:

These resources are used to supply the load demand, they are solicited in charging or discharging mode to ensure the power balance according to the frequency fluctuation. Equation (8) present the power changes in BES.

$$\Delta P_{BES} = \Delta f.G_{BES} = \Delta f.\frac{1}{1+T_{BES}.s} \quad (8)$$

We define the power fluctuation ΔP and the dynamic model of as follow:

$$\Delta P = \Delta P_{PV} + \Delta P_{WT} + \Delta P_{DEG} + \Delta P_{MT} + \Delta P_{FC} - \Delta P_{BES} - \Delta P_{Load} \tag{9}$$

$$\Delta f = \Delta P . G_{sys} = \Delta P \frac{1}{D + M.s} \tag{10}$$

3. Problem formulation

This paper deals with secondary frequency control based on PI controller. In fact, a classical PI controller is usually tuned by simple and classical methods like Ziegler Nichols method to have a best disturbance rejection. However, it's inappropriate in some cases because of the empiric values of controller parameters. For that reason, other methods are applied to characterize the PI controller parameters using EA. Tuning K_i and K_p using EA involves minimizing IAE of frequency deviation as objective function. The idea is to compare between PI-EA and to choose the two best EA to create a robust hybrid algorithm. Equation (11) illustrates the objective function employed using $x = [K_{p1}; K_{i1}; K_{p2}; K_{i2}]$ as variable decision and taking into account some constraints; bounds of decision variables and DERs output power. The mathematical model is illustrated in the followed equations (11-17):

$$F_{Obj} = \int_0^T |\Delta f|^2 dt \tag{11}$$

$$\left(K_{p_{j_{min}}}\right)_{j=1,2} \le \left(K_{p_j}\right)_{j=1,2} \le \left(K_{p_{j_{max}}}\right)_{j=1,2} \tag{12}$$

$$\left(K_{i_{j_{min}}}\right)_{j=1,2} \le \left(K_{i_j}\right)_{j=1,2} \le \left(K_{i_{j_{max}}}\right)_{j=1,2} \tag{13}$$

$$P_{DEG_{min}} \le P_{DEG} \le P_{DEG_{max}} \tag{14}$$

$$P_{FC_{min}} \le P_{FC} \le P_{FC_{max}} \tag{15}$$

$$P_{MT_{min}} \le P_{MT} \le P_{MT_{max}} \tag{16}$$

$$P_{BES_{min}} \le P_{BES} \le P_{BES_{max}} \tag{17}$$

where: $P_{DEG_{min}}$; $P_{FC_{min}}$; $P_{MT_{min}}$ and $P_{BES_{min}}$ are the minimum DG power values and $P_{DEG_{max}}$; $P_{FC_{max}}$; $P_{MT_{max}}$ and $P_{BES_{max}}$ are the maximum DG power value resumed in the followed Table.

Table 3. Minimum and maximum DG power values

Minimum power value (kW)		Maximum power value (kW)	
$P_{DEG_{min}}$	0	$P_{DEG_{max}}$	20
$P_{FC_{min}}$	0	$P_{FC_{max}}$	10
$P_{MT_{min}}$	0	$P_{MT_{max}}$	10
$P_{BES_{min}}$	-20	$P_{BES_{max}}$	20

Choosing the best EA is based on two principal criterions: global and local best search performances. The first one is the best objective function value, and the minimum iteration number is considered as the best according to this criterion. The second one is measured by the variance of the population in Eq. (18). In fact, EA stop of running when the candidate solution doesn't change, so the fitness function will stabilize then the variance of population.

$$S^2 = \frac{1}{N-1} . \sum_{i=1}^{N} (f_i - f) \tag{18}$$

Where N is the number of particles, f_i is the fitness values of the i^{st} individual and f is the mean of fitness values of population.

In the next sections 4 and 5, we will define the six EA adopted in this work and we will run and explore results to select the two best algorithms in the two criterions.

4. Evolutionary Algorithms

This paper presents some EA algorithms as genetic algorithm (GA), differential evolution (DE), harmony search (HS) and teaching learning-based optimization (TLBO).

4.1. Genetic algorithm

GA is a metaheuristic optimization inspired by natural selection process [16]. This algorithm is defined by three operators: mutation, crossover and selection used in the process of evolution of the optimal solution.

Where:
- Mutation is the first part of GA. It's inspired from biological mutation and create some changes in the individual from the previous population to have better candidate (solution). This process should have a low probability to not be turned to random search.
- Crossover is the second part of the GA also named recombination. It's used to combine the genetic information of two parents to generate new offspring.
- Selection is the last part of GA which individual genomes are chosen from a population for later breeding using the second operator. It's done by evaluating individuals according to the fitness function and catch the best individual for the next step or to stop the algorithm.

4.2. Particle swarm optimization method

Particle swarm optimization (PSO) is a metaheuristic algorithm accredited to Kennedy and Eberhart in 1995 [15]. It optimizes a problem defined by an objective function by generating generation to improve a candidate solution in very large spaces of candidate solutions, starting from a randomly population. This method consists on particles movement inspired from behavior of birds flocking and fiches schooling the search-space according to their position and velocity. The particle's movement is influenced by its local best-known position to reach the best-known positions in the search space. This is expected to move the swarm toward the best solutions. we define Velocity as:

$$V_{k+1} = w.V_k + b_1.(P_i - X_k) + b_2.(P_g - X_k)$$

variable decision: $X_{k+1} = X_k + V_{k+1}$
where:
V_{k+1} is the updated velocity, V_k is the actual velocity, w is the inertia weight, b_1 is the global learning coefficient, P_i is the global best particle, X_k is the k^{tk} particle, b_2 is the personal learning coefficient and P_g is the local best solution.

4.3. Differential Evolution

DE is an EA and a stochastic, population-based optimization algorithm introduced by Storn and Price in 1996 and developed to optimize real parameter, real valued functions. In this algorithm, population is constituted by agents who moves to reach the best position. It's composed by mutation, recombination and selection [21]. These parts are repeated until some stopping criterion is reached.

Where:
-Mutation: this step consists on creating a new vector named donor vector Vf_{G+1} from previous ones named target vectors X_i using a mutation factor F:

$$Vf_{G+1} = X_1 + F(X_2 + X_3)$$

-Recombination: It combines successful solutions from the previous generation to develop the trial from the target vectors and the donor vector from the previous step with a probability Cr.
-Selection: in this level, the target vector is compared with the trial vector and the one with the lowest function value is admitted to the next generation.

4.4. Teaching Learning-Based Optimization

TLBO algorithm is a teaching-learning process inspired algorithm based on the effect of influence of a teacher on the output of learners in a class [17-18]. It describes two basic modes of the learning: through teacher (known as teacher phase) and through interaction with the other learners (known as learner phase). In this algorithm, the population concerned are learners and the main goal is to converge into population with teachers.

Where:
- The teacher phase means learning of the students from the teacher who tries to help them to obtain good marks. However, learner's mark depends on the quality of teaching and the quality of students present in the class. The algorithm considers the best students as teachers and others as simple students.
Students are improved and hope to change their status to teachers (feasible solutions). New individuals of the population are considered as students.
- Student phase: Student learning relay on the randomly student's interaction with others. In this phase, a student is connected randomly with another student. If the second learner gain less knowledge than the first one, then he will move toward his colleague otherwise he will go away.
This process is repeated until satisfy the stopping criteria

4.5. Biogeography-Based Optimization

BBO [23] is the new approach to problem solving and shares some features with other biology-based algorithms. According to the theory of BBO, a good solution is related to an island with a high, HSI, and a poor solution signifies an island with a low HSI. High HSI solutions resist change more effectively than low HSI solutions. BBO is the study of migration, speciation and extinction of species. Mathematical models of BBO describes how a species migrates from one island (habitat) to another, how new species arise and how species become extinct. The BBO optimization algorithm is the first presented as an example of how a natural process can be generalized to solve optimization problems.

4.6. Harmony Search

HS is a music-based metaheuristic optimization algorithm [16]. The search process in optimization can be compared to a jazz musician's improvisation process. The objective is to produce the best or optimum by transforming the qualitative improvisation process into some quantitative rules by idealization, and thus turning the beauty and harmony of music into an optimization procedure through search for a perfect harmony.

5. Simulation results

In this section, we apply step variations to PV panels, to WT and to load (see Fig. 2 and Fig. 3). The six EA are run using MATLAB/Simulink software defining common population size of 50 individuals and maximum iteration is fixed on 200 iterations. Simulation results are presented in Table. 4 and frequency deviations at T=20s of the different EA are illustrated in Fig 4.

Table 4. Simulation results

Algorithm	Iteration	Variance	10^{-3} x Objective function
GA	71	2,35 x 10^{-15}	6,3669
TLBO	142	7,13 x 10^{-36}	8,4841
DE	118	7,74 x 10^{-16}	8,5321
PSO	151	1,76 x 10^{-19}	8,5601
HS	82	3,17 x10^{-31}	8.5876
BBO	200	1,41 x10^{-14}	8.6033

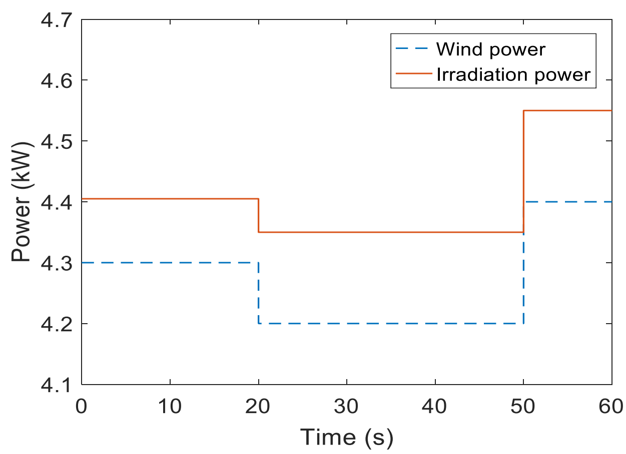

Fig 2. Wind turbine and irradiation power changes

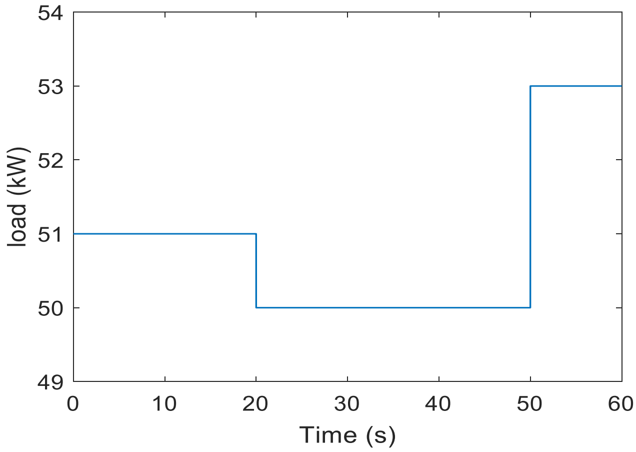

Fig 3. Load power changes

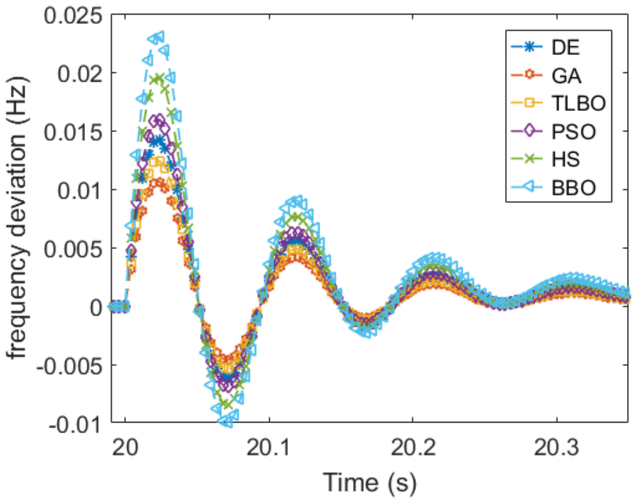

Fig 4. Frequency deviation using EA

According to the results in Table 4, GA is the fastest EA with the lowest objective function value and TLBO has the minimum variance value. The idea is to benefit from performances of both two EA by combining them (as explained in the previous section). This novel approach mixes the randomness of GA with its excellent global performance and local convergence of TLBO proved by the homogeneity of population with its low variance value of population. The application of this proposed method in reducing frequency deviation is the main contribution in this paper.

The hybrid algorithm benefits from the advantages of both of GA and TLBO by switching those two algorithms. In fact, GA makes a diversity in population due to the random aspect of this algorithm and creates an elite population but with some pour individuals. These worst solutions will be eliminated by the TLBO algorithm to save the best individuals and improve the worst. This alternance of these two algorithms are based on variance of population of solutions and by iteration value of each algorithm.

This proposed method starts by initializing the program parameter (defining population size, bounds of decision variable, GA and TLBO parameter) and random creation of initial population. Because of the excellent ability of global search, GA is the first algorithm to start and it's repeated until the variance of population will be less than Set Variance Value, then TLBO is run to eliminate poor individuals generated by GA. Despite of its best local search performance, TLBO can take much time and much iteration until reaching the stopping criterion. That's why the variation of the optimal fitness function F_{Obj} should be compared to a $Set\ F_{Obj}\ Value$ to switch or not to GA. The following figure illustrates the combined GA-TLBO algorithm explained. Parameter are selected as Set Variance Value=10^{-5}, $Set\ F_{Obj}\ Value$=10^{-5}, *Set_Cpt1*=5 and *Set_Cpt2*=5.

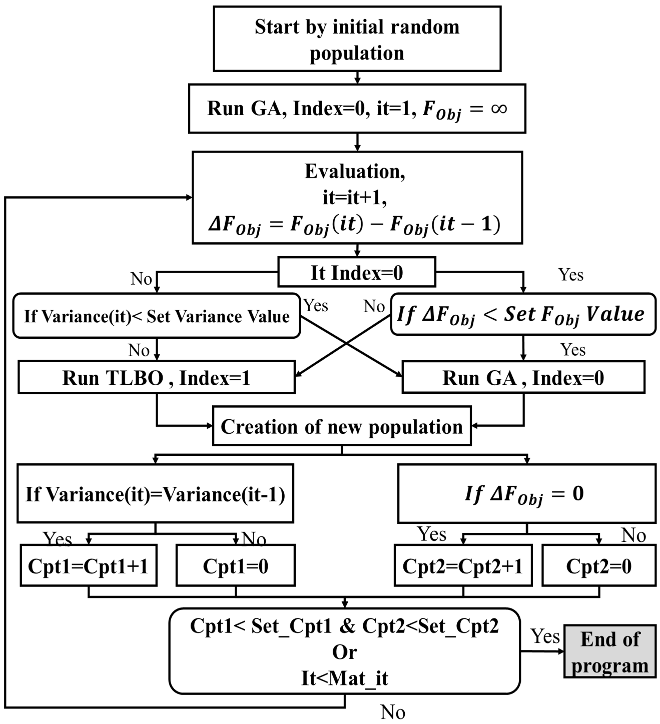

Fig 5. Flowchart of GA-TBLO algorithm

As shown in Fig 5, the proposed method starts by initialization of the first population, ΔF_{Obj} by infinity and let index=0 in the step 0. In the step 1, we calculate the fitness value of the population then we check if index=0 and ΔF_{Obj} and variance are less than their set values to select the EA to run (GA or TLBO) and create the next population. We define two counters Cpt1 and Cpt2 to calculate the consecutive iteration number respectively of GA or TLBO.

The program is ended if Cpt1 and Cpt2 are less than their Set values respectively Set_Cpt1 and Set_Cpt2 or the maximum of iteration is reached, otherwise we repeat the first step. Table 5 followed table illustrates the performance of the proposed method compared to GA and TLBO:

Table 5. Results proposed method

Algorithm	Iteration	Variance	10^3 x Objective function
GA	71	2,35 x 10^{-18}	6.3669
TLBO	142	$7{,}13\ x\ 10^{-36}$	8.4841

Proposed method: GA-TLBO	66	$5{,}96\ x\ 10^{-34}$	6,2571

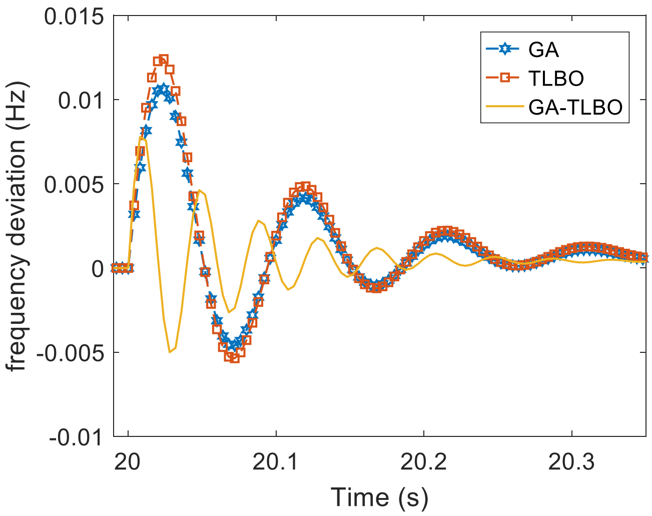

Fig 6. Frequency deviation using proposed method

5.1. Robustness of proposed method

To ensure the robustness of the proposed algorithm, MG parameters uncertainties are considered as illustrated in Tab 6.

Table 6. Variation of MG parameters

Parameter	Value	Parameter	Value
D (pu/Hz)	+40%	T_{FC} (s)	15%
M (pu)	+40%	T_{MT} (s)	-10%
T_{PV} (s)	+20%	T_t (s)	25%
T_{WT} (s)	+25%	T_g (s)	-35%
T_{BES} (s)	+20%		

A new scenario was established to test the accuracy of the proposed method under strict changes of MG parameters. A comparison between EA is illustrated in Fig. 7-8 and Tab 7-8.

Table 7. Simulation results under MG uncertainty parameters

Algorithm	Iteration	Variance	10^3 x Objective function
GA	68	$2{,}35\ x10^{-19}$	7.7365
TLBO	167	$9{,}04\ x10^{-28}$	7.7383
DE	136	$1{,}13\ x10^{-19}$	7.9040
PSO	200	$1{,}18\ x10^{-20}$	7.9406
HS	94	$3{,}68\ x10^{-17}$	7.9772
BBO	200	$4{,}45\ x10^{-13}$	8.2459

Table 8. Simulation results robust.

Algorithm	Iteration	Variance	10^{-3} x Objective function
GA	68	$2{,}35\ x10^{-19}$	7.7365
TLBO	167	$9{,}04\ x10^{-28}$	7.7383
Proposed method: GA-TLBO	61	$5{,}137\ x10^{-34}$	7.7275

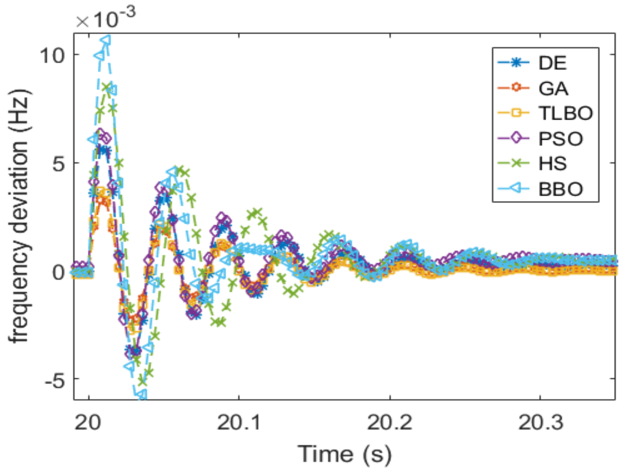

Fig 7. Frequency deviation using EA under uncertainty MG parameters.

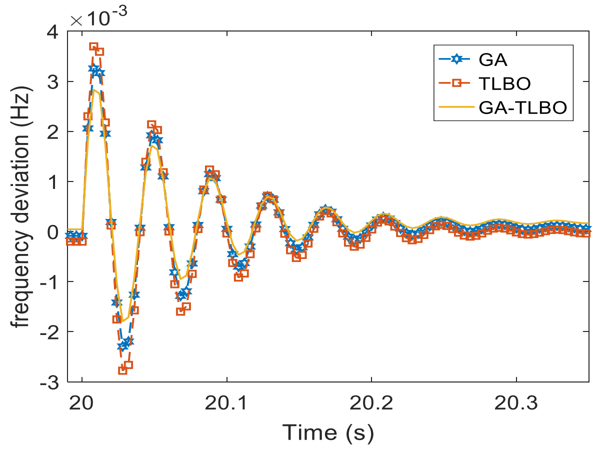

Fig 8. Frequency deviation using EA under uncertainty MG parameters

Simulation results confirm again that GA algorithm provide the best global performances with less iteration number then TLBO show its excellent local performance. That's why the proposed method hybrid GA-TLBO is accurate in front of the studied EA algorithms in this paper and presents the best values.

5.2. Simulation under uncertainty

In this part, a small perturbance is introduce to each DER of 10%. The goal is to validate the efficiency of the proposed method under uncertainty of inputs profile of non-controllable sources.

Under this uncertain perturbation, output power will be affected. As consequence, power balance will be destabilized then frequency deviation will be more important comparing to previous scenarios. Simulation results are shown in Fig 9-10 and Table 9-10.

Table 9. Simulation results under uncertainty

Algorithm	Iteration	Variance	10^{-3} x Objective function
GA	88	$4.35\ x10^{-10}$	12.9407
TLBO	133	$1.26\ x10^{-35}$	12.9707
DE	200	$6.65\ x10^{-11}$	12.9808
PSO	144	$3.27\ x10^{-30}$	13.0897
HS	156	$5.07\ x10^{-20}$	13.1484
BBO	200	$8.76\ x10^{-12}$	13.2593

Table 10. Simulation results of proposed method under uncertainty.

Algorithm	Iteration	Variance	10^{-3} x Objective function
GA	88	$4.35\ x10^{-10}$	12.9407
TLBO	133	$1.26\ x10^{-35}$	12.9707
Proposed method: GA-TLBO	81	$3.27\ x10^{-31}$	12.8824

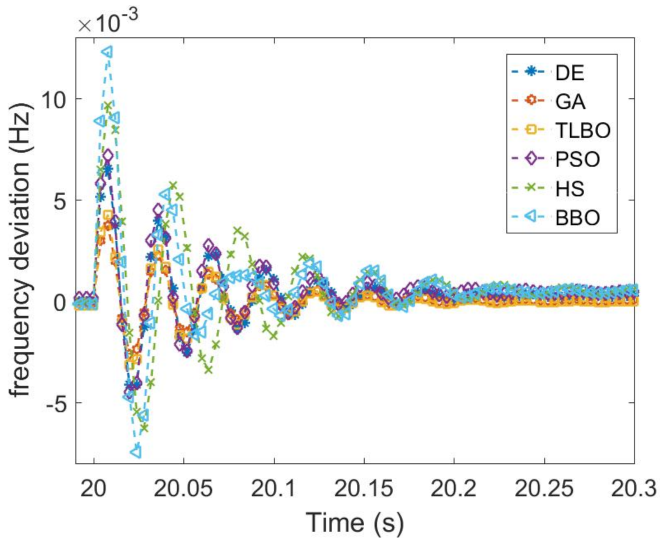

Fig 9. Frequency deviation using EA under uncertainty of output power

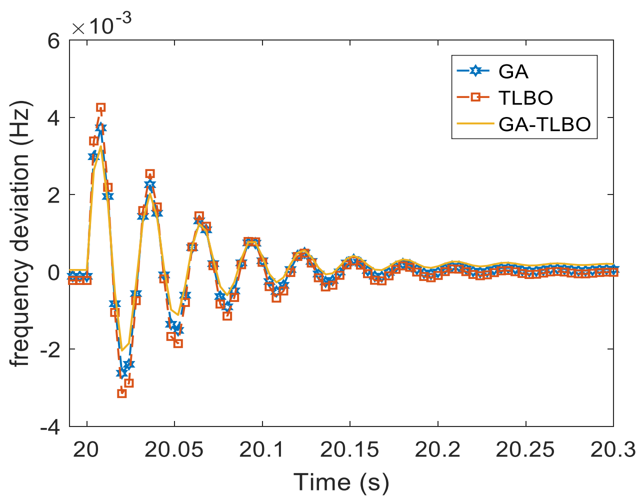

Fig 10. Frequency deviation using proposed method

According to the results, GA maintain its performance as the faster EA with the minimum Objective function and frequency fluctuation. By highlighting variance of population, TLBO conserve the best local behavior against other EAs. These conclusions demonstrate the combination between GA and TLBO as proposed method in this paper.

Table 9-10 show the efficiency of the proposed method with the minimum frequency deviation. In summary, results show that the proposed method searches out the optimal estimated values quickly and effectively than two other algorithms with uncertainty.

5.3. Simulation under variable Renewable power profiles

In general, MG deals with variable profile of irradiation, and load wind power unlike step profiles used specially to test controller performances. In this section we apply a variable random radiation, wind and load power profile as illustrated in Fig 11-13.

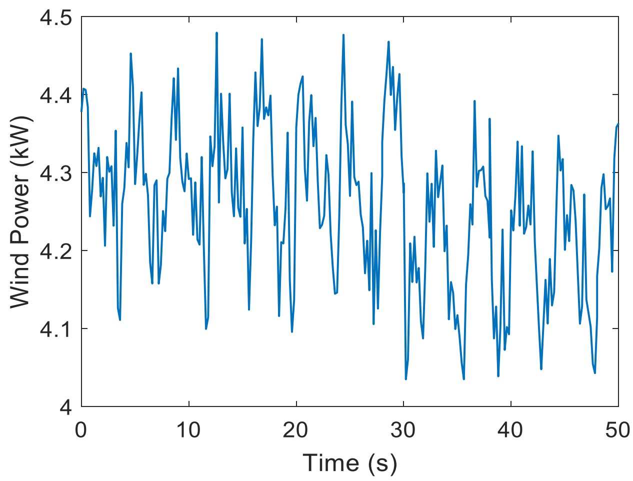

Fig 11. Wind turbine power variable changes.

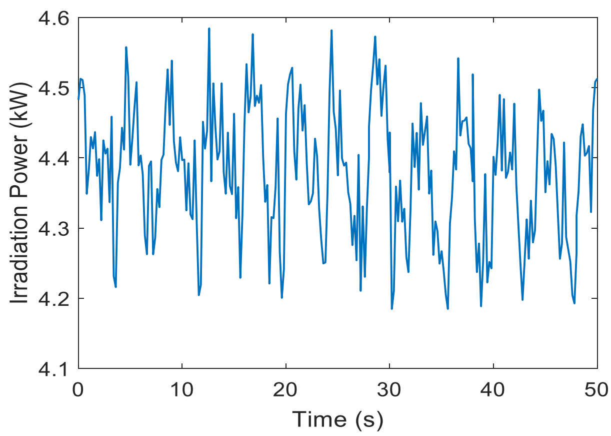

Fig 12. Irradiation power variable changes

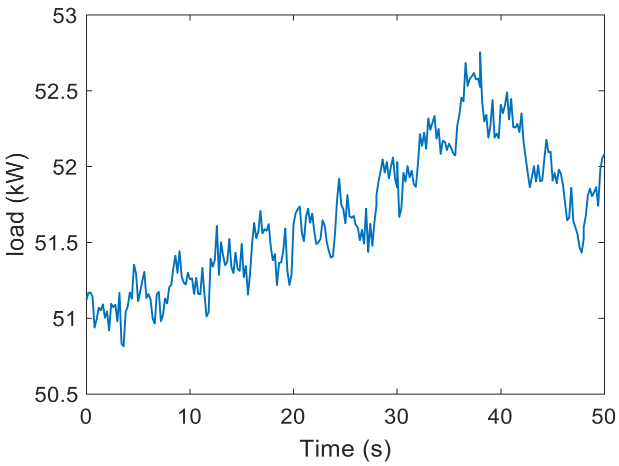

Fig 12. Load power variable changes

Table 11 shows results of classical algorithms and confirms the global best performances of GA and the local best performance of TLBO proved in the previous three scenarios. These results justify the combination of GA and TLBO in this case already presented in the first part of this section. In addition, the proposed method was compared to classical EA algorithms in order to verify its accuracy and best performance against other approaches and global resus are resumed in Table 12.

Frequency deviation of the six classical EA are illustrated in Fig 14 and a zooming between T1=29s and T=30s is presented in Fig 15 to compare easily these curves. Figure 16 contains only the two best classical EA and the proposed method. Fig 17 zooms the profile between T1=29s and T2=30s and reveals the robustness of GA-TLBO algorithm to minimize frequency deviation better than GA as the most efficient classical algorithm presented in this paper.

Table 11. Simulation results under variable WT and PV profiles.

Algorithm	Iteration	Variance	10^{-3} x Objective function
GA	102	$3.17\,x10^{-26}$	6.0904
PSO	170	$2.88\,x10^{-14}$	6.2977
BBO	200	$2.46\,x10^{-14}$	6.8829
DE	83	$1.27\,x10^{-32}$	7.0129
TLBO	76	$1.267\,x10^{-35}$	7.2029
HS	85	$3.17\,x10^{-26}$	7.2729

Table 12. Simulation results of proposed method under variable perturbations.

Algorithm	Iteration	Variance	10^{-3} x Objective function
GA	102	$3.17\,x10^{-26}$	6.0904
TLBO	76	$1.267\,x10^{-35}$	7,2029
Proposed method: GA-TLBO	63	$8.231\,x10^{-33}$	5,6584

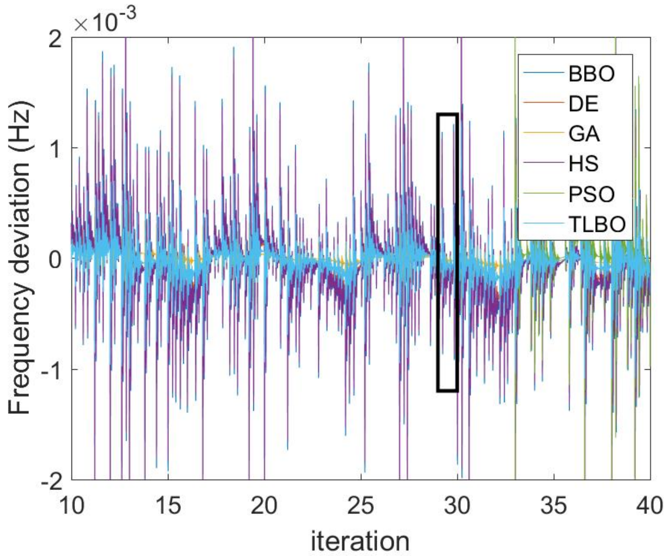

Fig 13. Frequency deviation using EA under variable WT and PV profiles

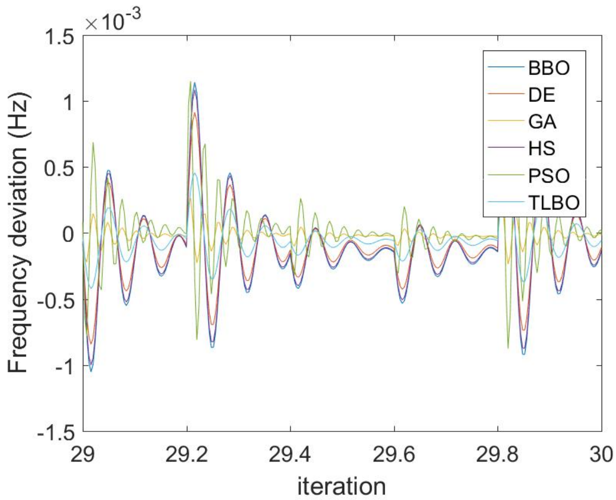

Fig 14. Frequency deviation using proposed method under variable WT and PV profiles.

This scenario is considered as the real scenario which can affect the MG. Referring to Fig 15, GA is the best EA in terms of cost function and according to Fig 16 the proposed method provide the minimum of frequency deviation compared to GA and TLBO. Tables 11 and 12 resume all results that confirm the robustness of the proposed method in local ang global algorithm performances.

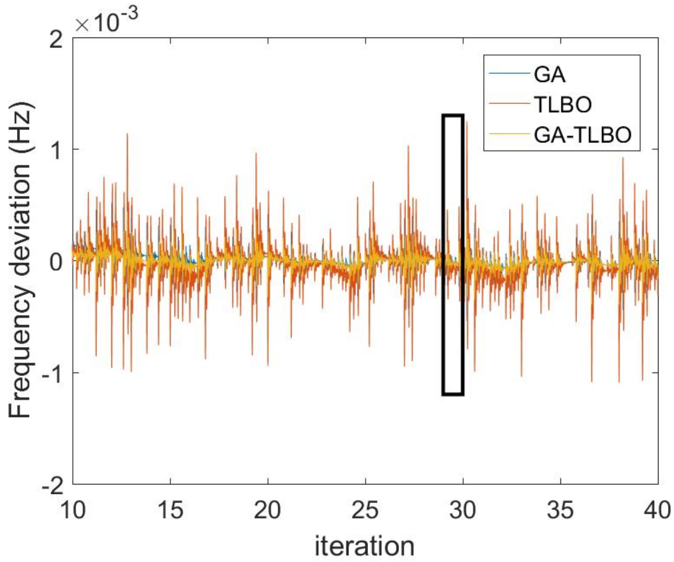

Fig 15. Frequency deviation using EA under variable WT and PV profiles at T=29s.

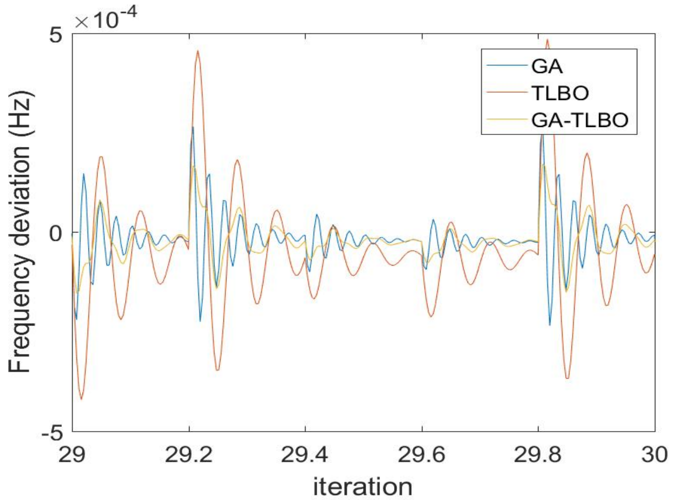

Fig 16. Frequency deviation using proposed method under variable WT and PV profiles at T=29s

6. Conclusion

In this paper, PI controller tuned by EA is used for secondary frequency control design problem in an autonomous MG. In order to control frequency deviation, a linearized MG state-space model is made. In the first part, a comparison between classical and EA tuned methods are done to make in evidence the accuracy EA taking into account the effects of ΔP_{wind}, ΔP_{irr}, and ΔP_{load} disturbances. As it shown, a novel GA-TLBO algorithm with cascade structure, which is used to minimize the frequency deviation with the intermittence of renewable and the variation load. The variance of fitness value of population as a criterion has been given to evaluate the population convergence and local convergence of population has been selected as the switching condition of TLBO to GA. Moreover, elite population replacement in GA is applied to TLBO to accelerate the convergence of population. Results from the simulations indicate that the proposed GA-TLBO algorithm represents a feasible and promising scheme for estimating the parameters of the equivalent admittance circuit model. Simulations about some similar algorithms have also been carried out. Comparing the simulation results, the GA-TLBO shows the best efficiency in frequency control in MG. Future work can include the forecasting of the considered perturbations; namely kinetic power, solar irradiation power and load demand to anticipate changes and reinforce frequency fluctuation in a more complex MG system.

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