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Development of Optimal PI Controllers of an Inverter–Based Decentralized Energy Generation System Based on Equilibrium Optimization Algorithm

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Abstract- The microgrid model gained considerable interest in the electricity industry due to increased financial and environmental benefits. The microgrid views decentralized generation (DG) and associated loads as a subsystem. The controlling methodology is the voltage source converter (VSC) cascaded-type converters technique, which depends on the Proportional-Integral (PI) controller. In this paper, the optimal tuning of the PI controller parameters is formulated as a constrained optimization problem for the system under different conditions (i) The system is converted from on-grid to off-grid mode at Time = 2 s. (ii) The system is subjected to three lines to earth fault in an off-grid mode. (iii) The system is subjected to load variation in an off-grid mode. The equilibrium optimization algorithm (EO) is physics-based optimization to tune the gains of the PI controller. The proposed approach (EO) has been compared with results from other approaches such as Genetic Algorithm (GA) which is inspired by a natural evolution process, Salp Swarm Algorithm (SSA) which is inspired by the swarming behaviour of salp in oceans. Simulations are conducted using MATLAB/Simulink software. The EO performs perfectly and has a fine ability to tune controller gains with smaller errors than other approaches.

Keywords Decentralized energy generation (DEG), equilibrium optimization algorithm (EO), Fitness function, Genetic Algorithms (GA), Salp Swarm Algorithm (SSA).

1. Introduction

The importance of energy lies in the transmission and distribution of electricity through overhead and underground cables at various voltage levels [1]. Networks must have meshed to make sure stable customer supply, even if individual pathways fail. But it's necessary to deal with the challenges of loss of energy on long tracks, which results in consumer suffering and affects the quality of the service.

Microgrids are one solution to this situation in the energy transition and their benefits include energy reliability, accessibility to energy, independence through renewable generation, and optimization of energy costs [2]. At this point, it is hard to predict the future of microgrids, but it seems likely that we are heading into a period where microgrids will be the rule and not the exception. The major equipment of microgrid which significant challenge that could help overcome the energy problems of the 21st century is a decentralized generation (DG). It is defined by his location for energy production closer to the energy consumption site [3]. The goal of decentralized energy systems is to minimize inefficiencies in transmission and distribution and associated economic and environmental costs [4].

Over the past two decades, the voltage source converter (VSC) has become the dominant structure for effectively controlled three-phase applications. The increasing usage of VSCs in variable-speed electric drive systems has aided this evolution. Due to the Pulse Width Modulated (PWM) function, VSCs working as active converters have low current distortion and reduced harmonic filter requirements, as well as the ability to regulate power factor and DC-link voltage [5]-[8].

A control strategy is based on the output voltage and frequency regulation to control the real and reactive power delivered from a DG to a local load [9]-[11]. The control strategy implements on DG unit controlled by PI controller [12]. This topology of the DG unit is constructed by supplying a two-level converter from a DC source, which is called a cascaded converter. The PI controller is preferred due to its simplicity and reliability as well as good performance [13].

Engineering design optimization appears to be very difficult, partly due to the complexity and extremely nonlinearity of the topic of interest. Optimization algorithms can be divided into many ways. One of them, there are two major categories according to their characteristics: (i) Deterministic, (ii) Stochastic [14], [15]. In another one, there are three categories of existing optimization methods: (i) the most well-known Meta-heuristics, (ii) recently developed algorithm, (iii) high-performance optimizers [16].

Optimization is everywhere with a wide variety of applications, is also an essential paradigm itself. We are always trying to optimize everything in almost all engineering and business applications, whether to minimize cost and energy usage or increase energy consumption, benefit, production, productivity, and success [17]. Resources, time, and money are often limited; optimization in practice is therefore much more important. It takes a qualitative change in scientific thought to maximize available resources since most real-world applications have much more complex variables and parameters to control how the system behaves.

Meta-heuristic algorithms are now among the most commonly used for optimization. They have many advantages over traditional ones [18]. It gains knowledge about the structure of optimization by using information obtained from the candidate solutions assessed in the past. This knowledge is used to build new candidate solutions that are likely to be of better quality. Meta-heuristics are generally classified into four types of inspiration: (a) evolutionary algorithms, (b) swarm intelligence, and (c) physics-based, and (d) human-based methods.

Several research papers have already been published in the literature that focused on detecting islanding issues in distribution systems using various methodologies and perspectives. E.C. Pedrino et al. presented Multi-gene Genetic Programming (MGP) for detecting DG islanding [19]. The islanding was accurately recognized and categorized by the MGP using their technique, which included the use of mathematics and logic capacities. The author demonstrated computational intelligence solutions for DG islanding detection. A. Rostami et al. [20], [21] proposed an islanding detection approach for synchronous DG. The concept was to run both the rate of change of exciter voltage (RCEV) and the open-close circuit breaker (OCCB) at the same time at a DG association point. The RCEV parameter was insufficient to effectively and precisely distinguish an islanding mode, so the author used the OCCB system. The process was practicable because the system only uses the CB at the DG and does not require any additional hardware, according to their methodology.

The Equilibrium Optimizer algorithm is used in this research to present a cascaded voltage source converter control for three-phase inverters in a microgrid. The proposed method initially formulates the three DGs in a microgrid as a standard constrained optimization problem, with decision variables consist of twelve parameters of decoupled PI controllers. The following are the significant contributions of this work: (1) the cascaded voltage source converter control method is applied first to the system under study. (2) The superiority of the proposed method EO is demonstrated and compared to GA and SSA by the simulation results for a system. (3) The system is tested under various operation conditions are a) It is required to convert to the islanding within two seconds after islanding with the equipment connected to it, b) The system is subjected to three lines to earth fault in an off-grid mode, c) the system is exposed to variant load in an off-grid mode. The sensitivity analysis of these methods is simulated in MATLAB for different operation conditions.The paper is structured as follows: In Section 2, the system is modeled. In section 3, the control methodology is detailed. In Section 4, the case study using EO, GA, SSA algorithms, and objective function are discussed. In Section 5, the simulation results and the comparative evaluation stage between EO, GA, and SSA techniques are demonstrated. Finally, the conclusions are stated.

2. Model Formulation

The system contains three DGs, each one is represented by a DC voltage source, a PWM, and a series filter. Three DGs are connected via a two-level converter to a utility grid. The three DGs and the grid are associated with the point of common coupling (PCC) to feed a local load. A delta-star step-up transformer is a principal link between the three DG and the grid. A three-phase parallel RLC network models the local load. For most off-grid detection methods, a Parallel RLC is a complex load class when the inductance and capacitance of load are set on the frequency system and the three DGs deliver their total power as shown Fig. 1.

When the three DGs and the local load separate from the grid, a disturbance may occur if the three DGs haven't a robust control strategy. The off-grid connected activity must be monitored and, therefore, voltage and frequency controlled to achieve continuous off-grid operation.

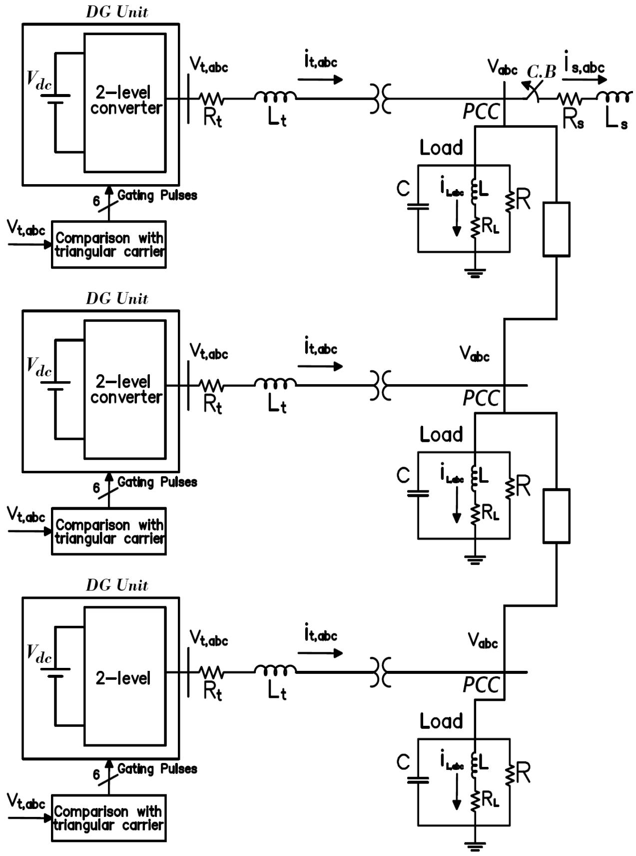


Fig.1 Schematic of the 3DG's microgrid.

Data of the three DGs, the Grid, and the rated load values that have been used in this analysis are listed in Table 1. The system works in both modes when it is connected on-grid or off-grid. The conversion of power between the three DGs and the grid is easily achieved by the (dq) frame current control. The on-grid and the potential off-grid will share real and reactive electricity. The system operates in a stable power condition when its values are zero.

Table 1. Parameter values of DEGs

Base Value		
Sbase = 1.6MVA	Vbase,low = 0.6kV	Vbase,high = 13.8kV
DER Rating		
DER1 = 1.6MVA	DER2 = 1.2MVA	DER3 = 0.8MVA
Transformer		
0.6/13.8	Δ/Yg	XT = 8%
Load Parameters		
Load1	Load2	Load3
pf= 0.96 Lagging	pf= 0.90 Lagging	pf= 0.94 Lagging
R1=350Ω = 2.94 P.U	R2=375Ω = 3.15 P.U	R3=400Ω = 3.36 P.U
XL1=41.8Ω=0.35P.U	XL2=37.7Ω=0.32P.U	XL3=45.2Ω= 0.38P.U
XC1=44.2Ω=0.37P.U	XC2=40.8Ω = 0.34P.U	XC3=48.2Ω=0.417P.U
RL1=2Ω=0.02P.U	RL2=2Ω=0.02P.U	RL3=2Ω=0.02P.U
Line Parameters		
R = 0.35Ω = 0.0029P.U Segment 1 = 5km		
X = 0.31Ω = 0.0026P.U Segment 2 = 10km		
Filter Parameters (based on DER1 Rating)		
Xf = 15% Quality Factor = 50		
Grid Parameters		
Xg = 2.3Ω = 0.024PU Rg = 2Ω = 0.021		

3. Control Methodology

The voltage source converter (VSC) cascaded-type converters technique uses the control loop for each of the three DEGs in the microgrid [22]. For on-grid connected mode, the purpose is to integrate the distributed generations(DGs) of low-voltage continuous current (DC) into the medium-voltage system [23],[24]. Since the converter does not dictate the grid voltage, this is achieved by controlling the current supplied by the converter to the grid. The control system required an accurate phase value for the grid voltage's fundamental component. The frequency and currents in the direct and quadrature axes (Id, Iq) are generated by a phase-locked loop (PLL) with the grid voltage as an input. Voltage angle δ and magnitude |V| of each DG. The output real power Pi and reactive power Qi of i-th module are derived as follows:

$$Pi = \sum_{k=1}^{N} |Vi||V\kappa|(Gi\kappa \cos \delta i\kappa + Bi\kappa \sin \delta i\kappa) \quad (1)$$

$$Qi = \sum_{k=1}^{N} |Vi||V\kappa|(Gi\kappa \sin \delta i\kappa + Bi\kappa \cos \delta i\kappa) \quad (2)$$

Otherwise, for the off-grid connected mode, the aim is to control the terminal voltages of direct and quadrature axis components (Vd, Vq). The output voltage is specified at the grid level as in [25], which defines Vrms to be within ±5% of the nominal voltage.

The control structure commonly used to achieve these is the two-loop control [26], [27], with an inner current and outer voltage loop as shown Fig 2.

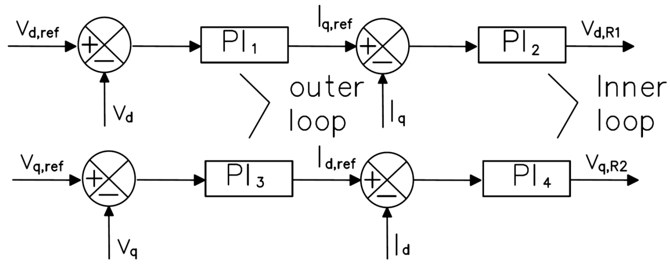


Fig.2 The cascaded voltage source converter mechanism for off-grid modes.

An internal oscillator is used to control the frequency of the system in an inner loop controller [28],[29]. The internal oscillator frequency is set at the nominal frequency of the system ω0. So as the frequency of voltage and current signals within the off-grid connected is predetermined in ω0. PWM the generator produces a triangular signal with constant value and compared to the reference voltages.

4. Case Study

This paper explores three optimization algorithms applied to the modeled system, which is simulated using MATLAB/Simulink software. The optimization algorithms include a recently developed optimization algorithm [30], called Equilibrium Optimizer (EO); GA as the most well-studied algorithm; and a swarm intelligence optimizer of SSA. The concept of the proposed System, how Transfer from on-grid connected to off-grid after constant time. In this task the PI parameters required for optimal microgrid operation to be utilized for each technique. The parameters for each algorithm are listed in Table 2.

Table 2. Parameter setting for algorithms

	Parameter	Value
EO	a_1,a_2	2,1
	Generation	0.5
	Type	Real coded
	Selection	Roulette wheel (Proportionate)
	Maximum iteration	50
	Number of search agents	24
GA	Crossover	Whole Arithmetic
	Mutation	Probability=0.8,α=[-0.5,1.5]
	Max_iteration	50
	Population size	20
SSA	Leader position update probability	0.5
	Maximum iteration	50
	Number of search agents	30

4.1. Proposed techniques

4.1.1 Genetic algorithms (GA)

It's inspired by the process of a natural evolution of generation improved to produce better solutions [31]. The technique chooses individuals as parents from the current population randomly and uses them to create children for the next generation. The population achieves an optimal solution over evolutionary generations as "good" parents generate "good" children. The "bad" points of the generation are eliminated. In general, the three major genetic factors, crossover, mutation, and selection of the fittest.

➢ Selection: is a competitive process that determines the use of fitness chromosomes as parents. Then these chromosomes will be used to produce new chromosomes as offspring.

➢ Crossover: acts as a binary operator, in general, new individuals are generated as the offspring of two parents. Inside within each parent's chromosome, one or more so-called crossover points (usually at random) are selected. The parts denoted by the crossover points between the parents are then overlapped. The individuals who generated are the offspring. There are several crossover styles beyond one point and multiple point crossovers.

➢ Mutation: By making modifications to one chosen individual, a new individual is created. That can be consist of modifying one or more values or adding/deleting parts of the representation. The mutation is a source of variability in GA, and the rate of very large mutations leads to less efficient development, except for the case of simple problems particularly [32].

The GA's illustrative flowchart Implementation of algorithms is presented in Fig. 3. [33].

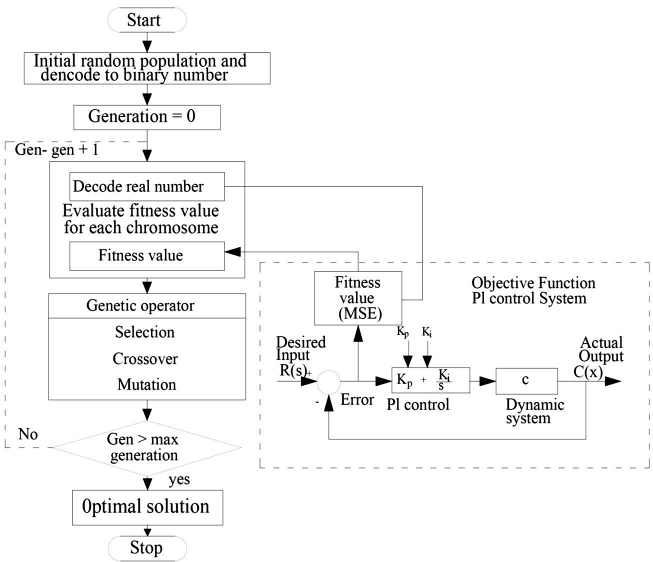


Fig.3 Flow chart of the general GA algorithm.

4.1.2 Salp swarm algorithm (SSA)

The algorithm of the Salp Swarm (SSA) has been proposed by Mirjalili et al as a population optimization technique. Salpes belong to the Salpidae family and have a translucent body in the form of barrels. Their shape and movement are very similar to jellyfish, where water is pumped into the body to move forward. The biological studies of these creatures are still in their early stages due to their very difficulty to access living environments and their difficulty in keeping them in laboratory environments. Their swarming behavior is one of the most interesting. In deep waters, salpes frequently form a swarm known as the salp chain. The standard model of salp chains is proposed [34], [35] to solve various problems with the optimization process. Mathematically, the salp chains are divided randomly into two groups of population: The first salp in Series is called leader, which is either explicit or implicit. The remaining salps are considered followers [36].

The SSA illustrative flowchart Implementation of algorithms is presented in Fig. 4.

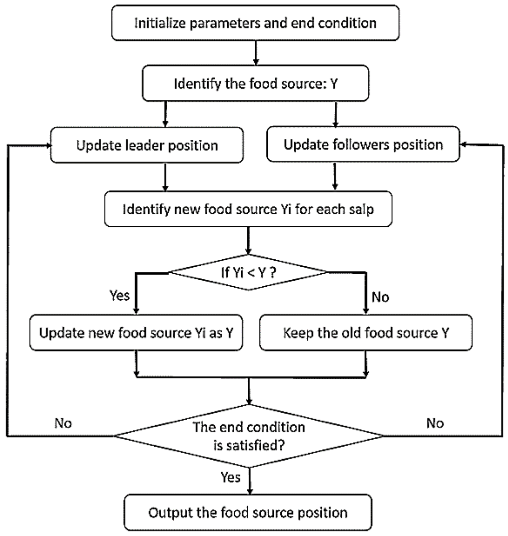


Fig. 4. Flow chart of the general SSA algorithm.

The SSA algorithm mechanism: [37]

➢ It saves and assigns the best solution to the food source variable, therefore, they are never lost even if the population is fully degraded.

➢ It only updates the leading salp position for the food source, which the best solution is found until now. So the leader always seeks to discover and taking advantage of the space around the best solution.

➢ It updates the follower slaps position for each other, so they follow gradually the leader salp.

➢ It cannot stagnate easily in local optima as a result of the progressive movement of followers slaps.

The SSA algorithm can effectively improve initial random solutions and converge to the optimal. It only has one parameter that gradually decreases to make the perfect equilibrium between diversification and intensification. The dynamic motions of salps improve the SSA's search capabilities to mitigate local optima and convergence defects.

4.1.3 Equilibrium optimizer (EO)

The equilibrium optimizer (EO) is the mass balance model of control volume used to about dynamic and equilibrium states [38], [39]. The EO algorithm has the advantage of being able to adjust the solution at random due to high exploration and exploitation. The particles and positions represent search agents. The search agents change their concentration at random concerning best-so-far solutions, which are called equilibrium candidates. That loop has repeated until it reaches the equilibrium state (optimal result).

The EO algorithm mechanism [40]:

➢ Initialization: EO generates initial candidates Cinitial random:

$$\left.\begin{array}{l}\text{For } i = 1{:}n_p \\ \quad C_{initial} = C_{min} + rand(C_{max} - C_{min})\end{array}\right\} \quad (3)$$

C_{min}&C_{max}: minimum & maximum values of concentration.

n_p : The number of particles.

rand: Number randomly created in range (0, 1).

➢ Assign a large number to the fitness of equilibrium candidates and let $a_1 = 2$; $a_2 = 1$; GP = 0.5. In all meta-heuristic algorithms, the fitness function is considered a key step. For solving tuning PI controller using EO, it must be provided with a function to evaluate the solution given by each particle in the group.

➢ Equilibrium Pool and Candidates CEq: there are five candidates for equilibrium. The first four are the best-so-far particles found during the process of optimization, which improved exploration capability. The fifth is the arithmetic mean of the first four, which focuses on exploitation.

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

➢ The exponential term F is the fundamental concentration update rule in EO. The term F can be calculated using the formula

$$F = e^{-\kappa(t-t_0)} \quad (5)$$

$$t = \left(1 - \frac{iter}{iter_{max}}\right)^{\left(a_2 \times \frac{iter}{iter_{max}}\right)} \quad (6)$$

$$t_0 = \frac{1}{\kappa}\ln\left(-a^1 sign(rand - 0.5) \times (1 - e^{-\kappa t})\right) + t \quad (7)$$

κ : The turnover rate.
t : selects appropriate values to control the rate of convergence
t_0 : The initial time
a_2 : Constant value controls the exploitation feature.
a_1 : Constant value that controls exploration feature.
$iter$, $iter_{max}$: The current number of iterations and the maximum number of iterations.
$sign(rand - 0.5)$: assisting with the direction control of the search.

Three terms provide the rules for updating the particle as shown Fig.5:

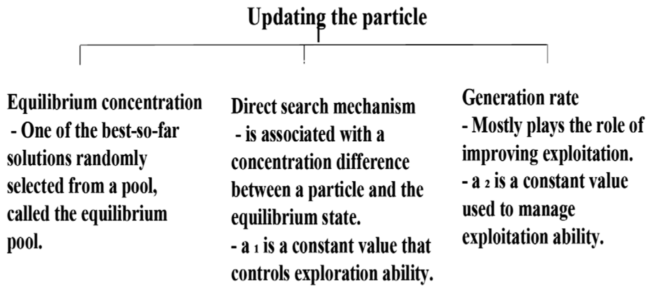


Fig. 5. Schematic of basic rules for updating the particle.

The EO illustrative flowchart Implementation of algorithms is presented in Fig. 6.

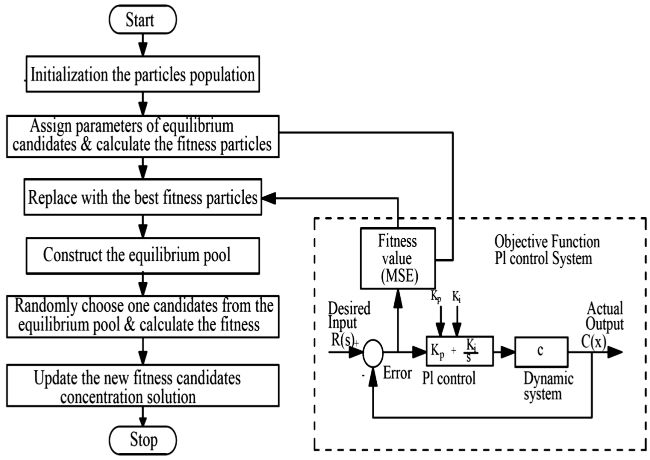


Fig. 6. Flow chart of the general EO algorithm [41].

4.2. Computational Complexity analysis

The computational complexity [42] of an optimization algorithm is expressed in the form of a function relating the algorithm's running time to the input size of the problem. For this purpose, Big-O notation is a typical word used for this purpose. To obtain a final shape, complexity is dependent on various parameters. Table 3 lists the parameters for each algorithm.

Table 3. Parameters & Complexity Function

	Complexity parameter	Complexity Function
EO	n: number of particles.	$O(EO) = O(1 + nd + tcn + tn + tnd) \cong O(tnd + tcn)$
	d: number of dimensions.	
	t: number of iterations.	
	c: cost of function evaluation.	
GA	n: number of Population.	$O(GA) = O(t(c + m)d + tcn) = O(tnd + tcn)$
	d: number of dimensions.	
	t: number of iterations.	
	c: number of offsprings.	
	m: number of mutated populations.	
SSA	n: number of solutions.	$O(SSA) = O(t(d*n + C*n))$
	d: number of dimensions.	
	t: number of iterations.	
	c: cost of objective function.	

Analyses show the increased complexity of the algorithms provides some advantages over the regular PI controller. Gains in performance are reducing as the delay capacity becomes slightly smaller than the process's time constant.

5. Simulation Result

5.1. Simulation study for PI controller of cascaded Voltage source converter

The system is modeled in the MATLAB /SIMULINK, in which the case study is divided to (i) the conversion from the on-grid connected to off-grid connected occurred at Time = 2 s. (ii) The system is subjected to three lines to earth fault in an off-grid mode. (iii)The system is subjected to load variation in an off-grid connected. EO, SSA, and GA are executed in the m–file which is interconnected to the SIMULINK model for simulation and obtaining the results to be utilized in computing the optimal PI controller parameter. The tuned PI parameters were tabulated in Table 4.

Table 4. Adjusted gain values of PI controller

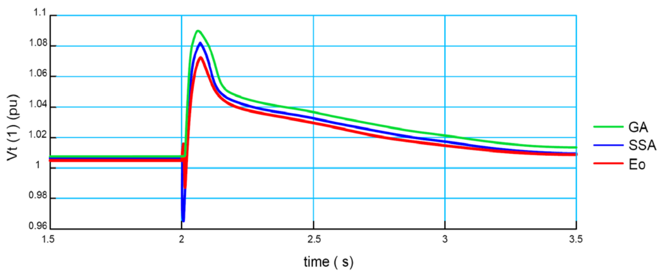
		PI No.	EO		GA		SSA	
			kp	ki	kp	ki	kp	ki
DG1	On-grid / off-grid	1	0.96	0.101	1.04	0.092	1.1682	0.1004
	(LLL-G) fault		0 .8	0.076	1.1	0.045	3.78	0.089
	Load variation		0.978	0.097	0.978	0.097	0.978	0.097
	On-grid / off-grid	2	0.118	1.06	0.118	1.18	0.1199	1.1671
	(LLL-G) fault		0.13	1.1	0.1	1	0.44	0.082
	Load variation		0.097	0.978	0.097	0.978	0.097	0.978
	On-grid / off-grid	3	0.5933	14.066	0.5667	14.0667	0.4455	16.1316
	(LLL-G) fault		0.876	12	0.5321	16.32	0.2376	18.453
	Load variation		0.489	14.89	0.489	14.89	0.489	14.89
	On-grid / off-grid	4	34.0667	0.5667	35.1333	0.5133	34.3133	0.3627
	(LLL-G) fault		32	0.783	21.114	0.341	23.023	0.546
	Load variation		34.897	0.489	34.897	0.489	34.897	0.489
DG2	On-grid / off-grid	5	0.0433	4.0667	0.0433	4.3333	0.0596	5.5269
	(LLL-G) fault		0.0768	2.45	0.04	5.421	0.0542	5
	Load variation		0.0489	4.89	0.0489	4.89	0.0489	4.89
	On-grid / off-grid	6	0.114	1.32	0.118	1.88	0.108	1.4052
	(LLL-G) fault		0.34	0.22	0.1	1	0.1	1.657
	Load variation		0.097	1.961	0.097	1.961	0.097	1.961

	On-grid / off-grid	7	0.7	26.4662	0.62	24.0667	0.6847	26.1949
	(LLL-G) fault		0.55	7	0.84	21.436	0.75	29.21
	Load variation		0.789	24.897	0.789	24.897	0.789	24.897
	On-grid / off-grid	8	34.0667	0.0163	36.2	0.0163	35.3478	0.0123
	(LLL-G) fault		33	0.023	33.432	0.03	38	0.008
	Load variation		34.897	0.0977	34.897	0.0977	34.897	0.0977
DG3	On-grid / off-grid	9	0.4333	0.0993	0.4333	0.0993	0.4184	0.0945
	(LLL-G) fault		0.403	0.1435	0.365	0.32	0.165	0.0678
	Load variation		0.489	0.097	0.489	0.097	0.489	0.097
	On-grid / off-grid	10	0.1087	0.0567	0.1087	0.0567	0.1001	0.0526
	(LLL-G) fault		0.098	0.034	0.11	0.0532	0.34	0.08
	Load variation		0.097	0.0489	0.097	0.0489	0.097	0.0489
	On-grid / off-grid	11	0.5667	8	0.5667	11.2	0.3276	8.6556
	(LLL-G) fault		0 .7	3.065	0.7423	10	0.341	12.435
	Load variation		0.489	9.61	0.489	9.61	0.489	9.61
	On-grid / off-grid	12	10.1333	0.094	11.2	0.0927	10.0421	0.1008
	(LLL-G) fault		8.54	0.2	9.6822	0.1	12.5	0.42
	Load variation		9.61	0.097	9.61	0.097	9.61	0.097

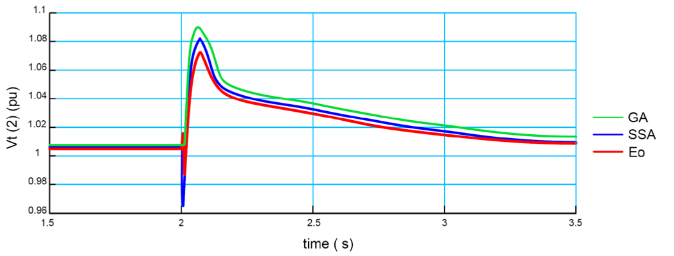
After adjusting the parameters using EO, SSA, and GA algorithms, a step change analysis was carried out with the help of the simulation environment. For models obtained with the designed controller, compare time field specifications with the output terminal voltage.

Figures 7-9. Display the simulated responses of the microgrid of various three DGs with different PI controller settings. The process response was observed by giving simulated results for the output terminal voltage (Vt) via each DG.

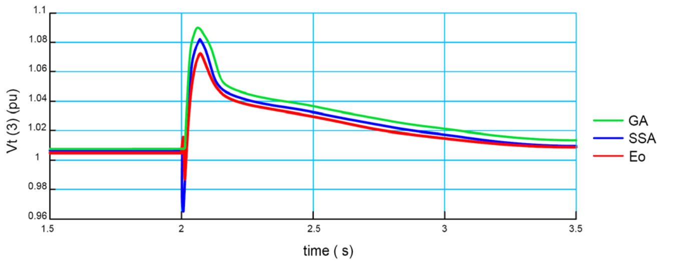
Case (1): the transfer from the on-grid connected to off-grid connected occurred at time = 2s.



(a)



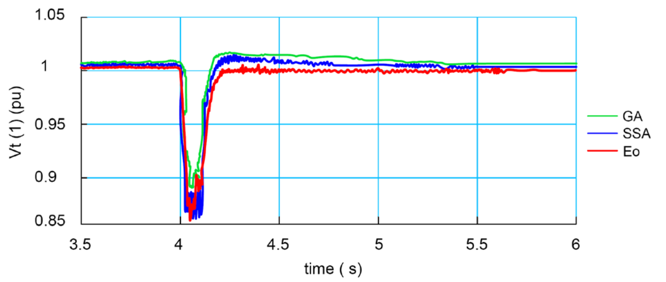
(b)



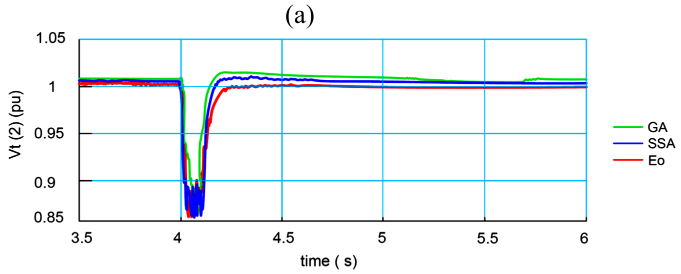
(c)

Fig. 7. Comparative terminal voltage profile (Vt) using suggested algorithms: (a) For DG1; (b) For DG2; (c) For DG3 under case (1).

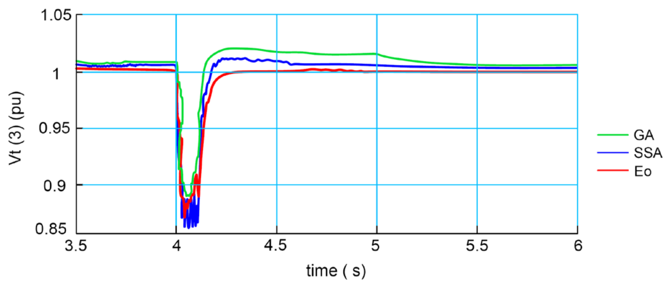
Case (2): The system exposes three lines to earth fault in an off-grid mode. Fault (LLL-G) occurred at t=4 sec. Fault clearance occurred after 0.1 sec.



(a)



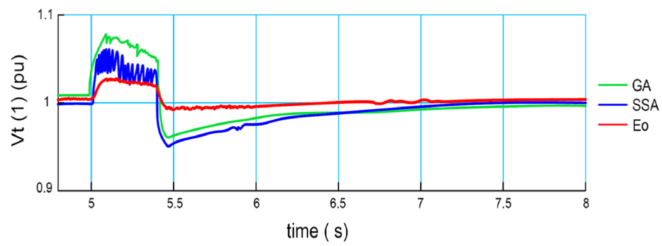
(b)



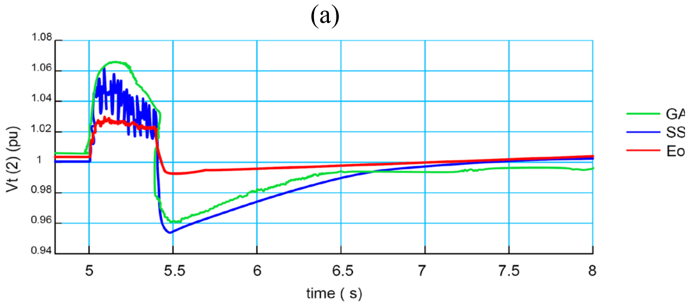
(c)

Fig. 8. Comparative terminal voltage profile (Vt) using suggested algorithms: (a) For DG1; (b) For DG2; (c) For DG3 under case (2).

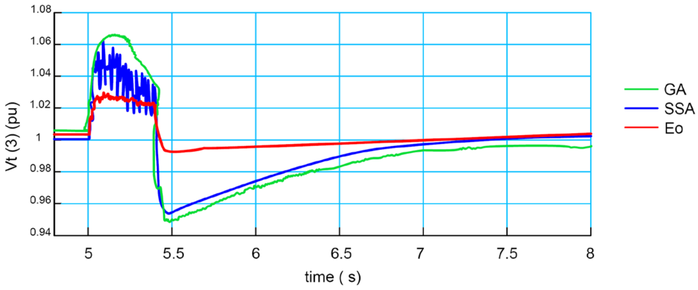
Case (3): The system exposes to load variation in an off-grid mode. The load resistance changes over the existing value by 152Ω at t= 5 sec for 0.4sec.



(a)



(b)



(c)

Fig. 9. Comparative terminal voltage profile (Vt) using suggested algorithms: (a) For DG1; (b) For DG2; (c) For DG3 under case (3).

- It is observed that from Fig. 7-9. The MPOS and MPUS are very low when applying the proposed EO algorithm for tuning the PI controller compared to the other algorithms. Also, the EO-PI technique possesses a better response in the transient period than the SSA & GA techniques.

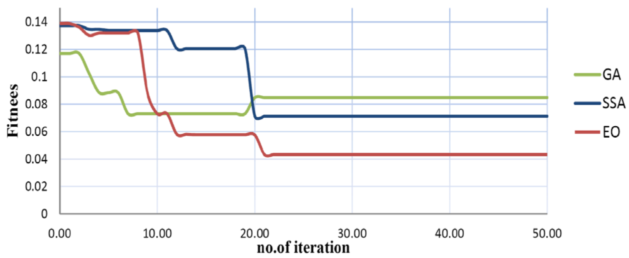
- It is noted from figure 7 that the voltage varied at the specified moment t = 2 seconds, the time of disconnection from the main grid. The voltage had decreased to 0.96 before being boosted to 1.09. SSA appears to be descending faster than EO, GA. However, EO is rapidly rising and making stability better for both SSA and GA.

- Fig. 8 that the EO algorithm improves the system response during the transient period for the microgrid during LLLG fault occurrence in the off-grid mode.

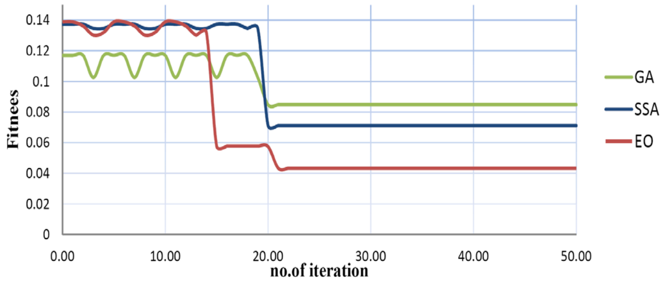
- Fig. 9 We can see that before t = 5s, EO, SSA, and GA showed similar performance. But after time t = 5s, GA, and SSA have the same shape and are followed by EO. EO show significantly better performance compared to GA, SSA.

5.2. Comparative convergence analysis

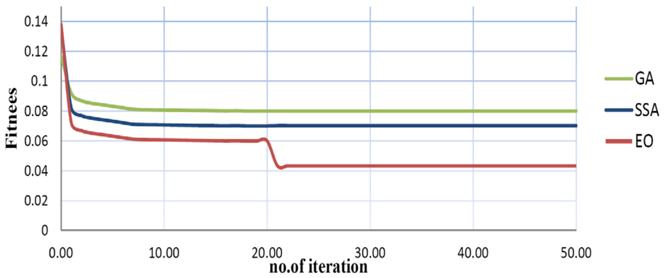
This study chose the optimal to obtain a brief and effective comparison of algorithms. To compare the performance of the algorithm in each mode category to optimize the parameters of PI controllers. Specifically, if the system has a target to minimize MPUS. A designed analytical MATLAB file and different fitness functions were tested to assess insight into this problem. It can determine and plot the shown in Fig.10, and Fig.11.



(a)



(b)



(c)

Fig. 10. Convergence comparison of suggested algorithms for the three proposals: (a) On-grid/off-grid; (c) the fault (LLL-G); (d) Off-grid.

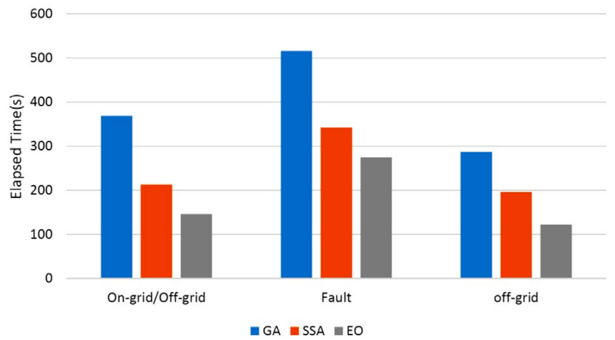


Fig. 11. Processing time of suggested algorithms.

A MATLAB file designed to draw the value of the objective function is applied under the influence of algorithms considered for adjusted PI controllers. It's worth noting from:

- Fig. 10(a, b, c) for each of the previous proposals, that the suggested EO-optimized the least minimum fitness value in considerable computation time, and exhibits better convergence mobility than other techniques.

- Fig. 10 (a) We can see that before iteration 10, EO and SSA showed similar performance, followed by GA. But after iteration 10, EO show significantly better performance compared to GA, SSA. The performance becomes the same stability for all methods after iteration 20.

- Fig. 10 (b) We can see that before iteration 20, EO and SSA showed similar performance, followed by GA. But after iteration 20, EO, SSA, and GA have the same shape. EO show significantly better performance compared to GA, SSA.

- Fig. 10 (c) We can see that before iteration 20, EO, SSA, and GA have the same shape. But after iteration 20, EO show significantly better performance compared to GA, SSA.

- Fig.11 shows that the suggested EO-optimized achieve the minimum processing time compared to other techniques.

6. Conclusion

This paper suggests a new optimized PI controller for improving the performance of a microgrid system with three DGs. The EO algorithm is effectively used to improve input measurement factors, output gains for the proposed PI controller. For the same case study, the effectiveness of the suggested EO-PI controller was compared with other algorithms such as GA and SSA algorithms. In addition, various scenarios have been implemented to verify the robustness and sensitivity of the proposed algorithms for different load variations, fault occurrence, and conversion of the system from on-grid connected to off-grid connected. The results proved that the proposed EO algorithm is more effective than the other algorithms because it provides the best fitness function of 0.043 while at GA 0.08 and SSA 0.07. As a result, the EO-PI controller outperforms algorithms in response time and fitness function in different scenarios. Variations in dynamic response specifications due to different variant loads (1 to 30%) and other system characteristics were also determined to be within an acceptable range, verifying the suggested controller's stability and performance robustness. For future studies, the proposed controller should be used to control different responses in a smart grid with different renewable sources and storage batteries.

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