Fault-Tolerant Optimization and Control of a Microgrid Operation in Networked Microgrids

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Abstract: - Networked microgrid operation and control is supported by fault-tolerant optimization. In networked microgrids, the microgrid failure or dysconnectivity from the network is obvious and must be rectified and restored in real-time. For this purpose, we need advanced algorithms for fault-tolerant optimization and its control in networked microgrids operation. We have introduced a multi-objective genetic algorithm (MOGA) to solve the multi-objective optimization problem. Genetic algorithms being meta-heuristic techniques are used to solve formulated complex optimization problems; fault-tolerant optimization problems (FTOP). A fault-tolerant optimization problem (FTOP) has the possibility of partial components of the system failing or generating errors during the operation of networked microgrids. For this problem, we have determined the best possible solution which is obtained even in the presence of failure or errors as well. We have minimized the total cost of the system and provision of a consistent supply of energy in case of failure of a microgrid in the networked microgrids to get stable and reliable energy. FTOP problems mostly occur in critical and uncertain systems like microgrids in which reliable power is the demand from the customers with continuous availability.

Key-Words: - Networked Microgrids, Fault Tolerant, Optimization, Operation Scheduling, Contingency, Distributed Control.

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1 Introduction

Clean, stable, and reliable energy availability is a need for progress and appropriate development of society and economy. In this context, microgrids are considered a key approach to provide neat and clean renewable energy to society. For this purpose, microgrids need to be more stable and have optimized operation to make the main grid, a smart grid. We can consider the microgrids model as the combination of energy generation, energy distribution, energy storage, and provision of energy to end-users. We can include objective functions, decision variables, and constraints to optimize its operation and control of fault tolerance. Mostly, genetic algorithms and simulated annealing optimization algorithms are used to optimize its operation, [1].

Microgrids provide power to main grids in order to support the end users in the context of power stability and availability. Fault-tolerant optimization and control of microgrids with respect to constraints can be performed at every instant even in the presence of faults. The moving horizon estimation approach and model predictive control (MPC) approach are used in order to maximize the profit and enhance the sustainability of microgrid operation, [2]. Similarly, we can enhance and improve microgrids' real-time operation by using model predictive control methodology taking into account stochastic fault-tolerant mechanism. We can perform optimization and control for the reconfiguration of faults by using model parameters, objective functions, and constraints using MPC, [3]. A fault tolerance scheme can be implemented by using hierarchical multi-agent system techniques in which a self-healing process can detect the fault and recover in case of any microgrid failure or in islanded mode status. Both the sentinel agent approach and computing of workload distribution approach are performed based on the sender-receiver communication strategy, [4]. The passive distribution networks are now changed into active distribution networks due to microgrids induction into the main grid networks. The fault currents are becoming bidirectional in which radial distribution network fault location and detection methodologies are no longer applicable. For this, we can use a correlation matrix for each microgrid individually connected to its topology like line, ring, or full. The probability of fault detection and its optimization can be performed by using bat-PSO like evolutionary algorithms, [5]. Having a lot of benefits, microgrids have a set of challenges and issues in their operation and control along with their fault rates. We can make the problem multi-objective when we talk about both optimization and control and fault tolerance of microgrids. Microgrid operation optimization and control can be achieved by following approaches as shown in Table 1.

Table 1. describes the techniques to optimize and control the microgrids' operation

Microgrid Optimization and Control Techniques	Conventional Methods
	Non-linear Methods
	Adaptive Methods
	Model predictive control Methods
	Optimal control Methods
	Robust techniques
	Intelligent techniques
	Fault-tolerant approach
	Centralized strategy
	Distributed strategy

In fault-tolerant mechanisms, there are active and passive fault-tolerant strategies which are applicable according to the requirements of energy usage. While replacement of the faults or faulty elements in the microgrids, we have both physical and analytical redundancy, [6].

In the case of networked microgrids, it is a most important thing to keep the power more stable and reliable because these factors are completely dependent on the microgrid configurations. Stability and reliability are based on consistent power flow as required in each case of networked microgrid configuration.

This paper consists of Section 2, which describes the optimization problem formulations that are going to be solved. Section 3 of this paper presents multi-objective cost functions formulation and determination of its fitness in order to optimize the fault tolerance. This mathematical formulation is solved by using Genetic Algorithms. Section 4 consists of simulations and validation of the outcomes. Section 5 discusses the conclusions of this research work and how it is connected to future work.

2 Problem Formulation: Fault-Tolerant Optimization for Scheduling Operation of Networked Microgrids

Networked microgrids are essential for the current smart grids. Their operation and trading schedules must be optimal in order to minimize the cost of operations and trading the energy according to the needs. In addition, a fault-tolerant optimization problem (FTOP) has the possibility of partial components of the system failing or generating errors during the operation. For such a problem, we need to determine the best possible solution which is obtained even in the presence of failure or errors as well. FTOP problems mostly occur in critical systems like microgrids in which reliability and availability of power are key factors even in cases of uncertainty.

There are the following generic steps that can be used to formulate the FTOP problem:

1. **Problem Definition:** Description of the system objective that is under consideration and its variables/parameters used in the optimization process.
2. **Critical Components Identification:** Finding components of the system that have the most probability of failing and identifying the operating states of the system like failed or operational.
3. **Objective Function:** Defining the objective function which is to be optimized. There are two categories of objective functions: single-target or multi-target functions according to the requirements like maximizing system availability or performance and minimizing operational costs.
4. **Constraints:** We need to introduce or set system limitations like availability of resources, time constraints, etc. These constraints are necessary to take care about the possible outcomes in the form of system failure.
5. **Failure Modelling:** Model development in order to represent the failure probability of each component of the systems and its effects on the

overall performance of the system like Markov models, liability models, Petri net models, etc.

6. Formulate Optimization Problem: The information obtained from the previous steps is to be used to formulate the optimization problem. It consists of decision variables, objective functions, and constraints relevant to fault tolerance.

7. Optimization Algorithm Selection: In this step, we need to select the relevant and appropriate optimization algorithm in order to solve the formulated problems like particle swarm optimization, genetic algorithms, etc.

8. Algorithm Implementation and Evaluation: The selected algorithm is implemented on a selected model from previous steps. Then the obtained results are evaluated. We need to perform consistent and extensive testing of the model and algorithm in order to ensure the solutions robust and they are operating according to the fault tolerance needs.

To formulate FTOP, we should consider the complexity of the system, reliability, and availability of the system is compulsory for its appropriate functioning.

The energy equilibrium between the networked microgrids can be written as:

$$E_i^{(c)} + E_{i,k} = E_i^{(g)} + E_{k,i} \tag{1}$$

and equilibrium under contingency or fault (we are going to consider as a fault in this paper, a microgrid contingency able to turn off the microgrid):

$$E'^{(c)}_i + E'_{i,k} = E'^{(g)}_i + E'_{k,i} \tag{2}$$

In this way, the energy equilibrium can be found by sum of energy consumed locally ($E_i^{(c)}$) and the energy sold to other networked microgrid ($E_{i,k}$) must be equal to the sum of energy generated by the microgrid $E_i^{(g)}$ and what energy is bought from other microgrid, not only in the normal operation but also in a contingency of microgrid 'j' ($E'^{(c)}_i, E'_{i,k}, E'^{(g)}_i, E'_{k,i}$).

The FTOP proposed in this research is the minimization of total cost function given by equation (3).

$$C = \min_{E_{1,2},E_{2,1}} \sum_{i=1}^{2} C_i\left(E_i^{(c)} + E_{i,k} - E_{k,i}\right) + \sum_{i=1}^{2} \gamma\left(E_{i,k}\right) \tag{3}$$

Subject to: $E_{1,2} \geq 0, E_{2,1} \geq 0$

$$E_i^{(c)} + E_{i,k} - E_{k,i} \geq 0$$

$where\ i = 1,2\ \&\ j \neq i$

$$E'^{(c)}_i + E'_{i,k} = E'^{(g)}_i + E'_{k,i}$$

$$(with\ microgrid\ 'j'\ in\ failure)$$

There are two cost functions used to formulate the total cost function. First cost function $C_i\left(E_i^{(g)}\right)$ is the price of each microgrid in order to generate energy $E_i^{(g)}$. The second cost function $\gamma\left(E_{i,k}\right)$ shows the cost of transporting $E_{k,i}$ from one microgrid to other microgrid, [7].

In order to handle this formulation using a combination of centralized and distributed approaches, [8]. The centralized approach applicable to convex and non-convex target functions can be developed by the Lagrangian of problem formulated in equation (3) as follows in (4).

$$\mathcal{L}\left(\{E_{i,j}\},\{\mu_i\},\{\mu_{i,j}\}\right) = \sum_{i=1}^{2} C_i\left(E_i^{(c)} + E_{i,k} - E_{k,i}\right) + \sum_{i=1}^{2} \gamma\left(E_{i,k}\right) - \sum_{i=1}^{2} \mu_i\left(E_i^{(c)} + E_{i,k} - E_{k,i}\right) - \sum_{i=1}^{2} \mu_{i,k} E_{i,k} \tag{4}$$

where:
We have introduced the following four multipliers:

$$\mu_i, \mu_{i,k}, i = 1,2\ and\ j \neq i$$

For a Distributed Approach (with microgrid j in failure), we have the constraint presented in (5):

$$constraint \rightarrow E'^{(c)}_i + E'_{i,k} = E'^{(g)}_i + E'_{k,i} \tag{5}$$

For the distributed approach, we have considered a relaxing the coupling constraint and introducing the Lagrange multipliers ($\lambda_{i,k}$), [9]. In this way, this part is formulated as a minimization problem in the following form (6):

$$\min_{\left\{E'^{(s)}_{i,k}\right\},\left\{E'^{(b)}_{k,i}\right\}} \sum_{i=1}^{2} \left[C_i\left(E'^{(c)}_i + E'^{(s)}_{i,k} - E'^{(b)}_{k,i} + \gamma(E'^{(s)}_{i,k}\right) + \lambda_{i,k} E'^{(s)}_{i,k} - \lambda_{k,i} E'^{(b)}_{k,i}\right] \tag{6}$$

Subject to: $E'^{(s)}_{i,k} \geq 0, E'^{(b)}_{k,i} \geq 0$

$$E'^{(c)}_i + E'^{(s)}_{i,k} - E'^{(b)}_{k,i} \geq 0\ ;$$

$where\ i,j = 1,2\ and\ j \neq i$ (with a microgrid in failure)

2.1 Advantages of the Proposed Fault-Tolerant Optimization Problem

The operator of the power system is responsible in order to define the quantity of power generation, sell and buy scheduling interval for each microgrid of networked microgrids and to keep the system working under a contingency. There are several advantages in networked microgrids operation and trading schedules when we consider a security/contingency constraint with the proposed formulation.

1. The cost functions of networked microgrids operations and trading schedules are not to be compulsory to increase monotonically, convex and twice differentiable, that is to say, it is possible to work with non-convex uncertainty cost functions as in the case of FTOP.
2. The cost functions proposed to handle in this paper of networked microgrids are supporting the uncertainty of primary renewable energy sources like wind energy and solar energy.
3. When one or two microgrids are in failure or isolated form networked microgrids, then the energy exchange between them is complex with respect to cost minimization which consists of energy generation and transportation along with fulfilling the local energy demand, [10]. Thus, the operator can operate the system under contingency.
4. In FTOP, we can enhance the reliability and availability of the power to the customers by increasing the profitability and minimizing the financial costs in networked microgrids.
5. The redundancy and backup plans in networked microgrids can enhance the data integrity and reliability.

3 Mathematically Formulation of Multi-Objective Cost Functions

We have formulated the multi-objective cost functions as a minimization of fitness functions. The formulated fitness functions have the ability to perform the evaluation steps for fitness to check the set of decision variables. These decision variables are scheduling of microgrid operation in case of normal operation along with having the ability to support a microgrid failure (fault tolerance). In fault tolerance case, the fitness function performs the evaluation process on a set of variables called Lambdas (represents price) for specific generating units in power systems subject to certain constraints and topologies of networked microgrids.

The aptitude function working is explained step by step as follows:

- **Global Configuration:** The function consists of certain global variables that must be initialized.
- **Assignment of Lambda:** These are the variables describing the potential price in context of interchanges within the microgrids.
- **E_gen Calculations:** These calculations are the net energy generations. The net energy generations can be found by summing up all generators' generations and then subtracting the total energy sold.
- **Cost Calculations:** The total energy cost is calculated for each microgrid in networked microgrids which is consisting of two parts, the operating cost of generator/microgrid and the cost of energy transfer.
- **Penalty:** A penalty cost is calculated, and it is the difference in operating cost and transfer cost as mentioned above.
- **Adjustment of Topology:** The topology of networked microgrids is adjusted accordingly with configuration establishment.
- **E_gen and Pmax Recalculations:** For each new topology of networked microgrids, we can recalculate the net energy generation E_gen and maximum power limits Pmax.
- **Exceeded Capacity Calculations**: We can calculate the exceeded capacity for each networked microgrid or generator in order to check if this generation is in excess from the maximum power limit allowed. These calculations are in case of microgrid failure.
- **Final Fitness Calculations:** The final fitness is the sum of the total cost, penalty, and exceeded capacity.

In brief, fitness function represents the evaluation of quality of a set of Lambdas-generation capacity for specific microgrids in networked microgrids. The fitness function is considering the operations of microgrids in networked microgrids, constraints of power, and topology of networked microgrids. This fitness function is basically used in a genetic algorithm in order to determine the optimal set of Lambdas. This set of lambdas is minimizing the fitness function making the operation of networked microgrids more efficient and reliable.

3.1 Cost Functions

The cost functions are used to calculate the cost of the system. There are two cost functions which are formulated in this problem: Local cost function and uncertainty cost function.

3.1.1 Local Cost Functions Problem

In this part, we have considered this cost function as a local microgrid optimization problem because the calculations are carried out locally at a microgrid of networked microgrids. We can find out [E_sell, E_buy] locally at a microgrid of networked microgrid and further solve it for minimization of cost which leads to optimal values of energy sold [E_sell] and energy bought [E_buy] for the microgrid under consideration. The local cost function constraints values are shown in Table 2.

Table 2. Represents the constraints values for local cost function

Ec1	Gen1	Pmax1	Ec2	Gen2	Pmax2	Ec3	Gen3	Pmax3	Ec4	Gen4	Pmax4
11	U12	10	11	U12	10	11	U12	10	1	U12	10
11	U12	10	11	U12	10	11	U12	10	2	U12	10
11	U12	10	11	U12	10	11	U12	10	3	U12	10
11	U12	10	11	U12	10	11	U12	10	4	U12	10
11	U12	10	11	U12	10	11	U12	10	5	U12	10
11	U12	10	11	U12	10	11	U12	10	6	U12	10
11	U12	10	11	U12	10	11	U12	10	7	U12	10
11	U12	10	11	U12	10	11	U12	10	8	U12	10
11	U12	10	11	U12	10	11	U12	10	9	U12	10
11	U12	10	11	U12	10	11	U12	10	10	U12	10
11	U12	10	11	U12	10	11	U12	10	11	U12	10

We have the following input in the system for local cost functions and its optimization:

- E_c is a positive real value energy load at the microgrid.
- E_buy is a logical vector values indicating the current microgrid which microgrid can buy and which microgrid cannot buy.
- E_sell is also a logical vector values describing the current microgrid which can sell energy or not.
- Lembda_sell is a real value of energy selling price in $/MWh.
- Lambda_buy is a real value vector having energy buying prices from other microgrids in the systems $/MWh.
- C_prime is the first derivate of generation cost function of networked microgrids. (required power (in MW) to a generation cost (in $/h).
- C_primeInv is the inverse function of C_prime.
- Gamma_prime is the first derivate of transfer cost function. (transferred power (in MW) to the corresponding transferring cost (in $/h).
- Gamma_primeInv is the inverse function of gamma_prime.

3.1.2 Uncertainty Cost Functions

The renewable energy resources like solar and wind energy along with electric vehicles have uncertainty in availability of power. These resources produce stochastic behavior in each dispatch model. In order to handle this problem, we need to introduce probability distribution functions (PDF) with uncertainty penalty costs calculations, [11].

We have considered uncertainty cost functions based on wind power generation. We can quantify the economic impacts of uncertainties based on uncertainties cost functions. The fluctuations in wind speed are supposed to be one of these uncertainties for power generation and distribution. We can breakdown the uncertainties cost functions which are used in code while doing this research work, [12].

Cost due to underestimation (CU):

The underestimation cost function represents the cost when we have less scheduled power (W_S) than the actual power output (W) from wind turbines.
This cost function can be represented as follows:

$$CU = C_u * (W - W_s) \quad (7)$$

where C_u is defined as cost per unit for power underestimation while $(W - W_s)$ is considered as shortfall in power generation as compared with the scheduled power.

Cost due to overestimation (CO):

Cost function due to overestimation can be considered when the actual power output (W) is less than the scheduled power (W_S).

This cost function can be represented in the following form:

$$CO = C_o * (W_s - W) \quad (8)$$

where C_o represented as cost per unit for power overestimation while $(W_s - W)$ is considered as an excess in power generation more than the scheduled power.

Such cost functions represent financial consequences of variations in actual and scheduled power generations. This concept provides in-depth knowledge about the economic risks related to the uncertainty in the case of wind power generation.

We can develop analytical expression in case of wind energy as follows:

3.1.2.1 Penalty Cost due to Underestimate for WEG Case

We have determined the uncertainty cost function (UCF) part which is related to the penalty cost occurred due to the underestimation, we have determined the following integral for this purpose, [13], [14]:

$$E\left[C_{w,s,i}\left(W_{w,s,i}\,,W_{w,i}\right)\right] = \int_{W_{w,s,i}}^{W_r} C_{w,u,i}\left(W_{w,i} - W_{w,s,i}\right).f_w\left(W_{w,i}\right)dW_{w,i} \quad (9)$$

where:

- $E\left[C_{w,s,i}\left(W_{w,s,i}\,,W_{w,i}\right)\right]$ is known as the expected value of penalty cost occurred due to underestimation.
- $f_w(W_{w,i})$ is the probability distribution function of power generated by wind energy generator (WEG) *i*.
- $C_{w,u,i}$ is called coefficient of penalty cost occurred due to the underestimation by wind energy generator (WEG) *i*.
- W_r is called maximum power output of the wind energy generator (WEG) *i*.
- $W_{w,s,i}$ is called the scheduled wind energy generated power by the generator *i*.
- $W_{w,i}$ is called (WEG) power available in the generator *i*.

The solution of integral equation (9) can be written in the following form:

$$E\left[C_{w,s,i}\left(W_{w,s,i}\,,W_{w,i}\right)\right] = \frac{C_{w,u,i}}{2}\left(\sqrt{2\pi}\,\rho\sigma\left(\mathrm{erf}\left(\frac{W_{w,s,i}-k}{\sqrt{2}\rho\sigma}\right)\right) + 2\left(W_{w,s,i}, W_r\right) - e^{-\left(\frac{W_r-k}{\sqrt{2}\rho\sigma}\right)^2}\right) + \frac{C_{w,u,i}}{2}\left(e^{-\frac{V_r^2}{2\sigma^2}} - e^{-\frac{V_0^2}{2\sigma^2}}\right)\left(W_r - W_{w,s,i}\right) \quad (10)$$

3.1.2.2 Penalty Cost due to Overestimate for WEG Case

We have determined the uncertainty cost function (UCF) part which is related to the penalty cost occurred due to the overestimation, we have determined the following integral for this purpose, [13], [14]:

$$E\left[C_{w,o,i}\left(W_{w,s,i}\,,W_{w,i}\right)\right] = \int_0^{W_{w,s,i}} C_{w,o,i}\left(W_{w,s,i} - W_{w,i}\right).f_w\left(W_{w,i}\right)dW_{w,i} \quad (11)$$

where:

- $E\left[C_{w,o,i}\left(W_{w,s,i}\,,W_{w,i}\right)\right]$ is known as the expected value of penalty cost occurred due to overestimation in case of WEG.
- $f_w(W_{w,i})$ is the probability distribution function of power generated by wind energy generator (WEG) *i*.
- $C_{w,o,i}$ is called coefficient of penalty cost occurred due to the overestimation by wind energy generator (WEG) *i*.
- $W_{w,s,i}$ is called the scheduled wind energy generated power by the generator *i*.
- $W_{w,i}$ is called (WEG) power available in the generator *i*.

The solution of integral equation (11) can be written in the following form:

$$E\left[C_{w,s,i}\left(W_{w,s,i}\,,W_{w,i}\right)\right] = C_{w,o,i}W_{w,s,i}.\left(1 - e^{-\frac{V_i^2}{2\sigma^2}} + e^{-\frac{V_0^2}{2\sigma^2}} + e^{-\frac{k^2}{2\rho^2\sigma^2}}\right) - \frac{\sqrt{2\pi}C_{w,o,i}\rho\sigma}{2}\left(\mathrm{erf}\left(\frac{W_{w,s,i}-k}{\sqrt{2}\rho\sigma}\right) - \mathrm{erf}\left(\frac{-k}{\sqrt{2}\rho\sigma}\right)\right) \quad (12)$$

3.2 Optimization using Genetic Algorithm

There are many applications of multi-objective genetic algorithms for the optimization of both energy generation and distribution in microgrids. We can improve the scheduling of distributed generation for a reduction in losses and improvement of voltage. Similarly, we can plan the power distribution grid based on the conditions of optimal power generation configuration, minimizing power losses, power transfer capacity, and overall optimal benefits in microgrids using a multi-objective genetic algorithm. An intelligent microgrid operation and control management system can support optimal power generation configuration, power sell and buy, and operating costs. There are several objectives while applying genetic algorithms to the problem. The location of the fault, the size of the fault, and the cost of the fault are considered major factors of fault tolerance. To handle these issues, we can use genetic algorithm for the optimal location of the fault, optimal size of the fault, and optimum price of the fault. In the case of optimization using the genetic algorithm, we need to keep the number of iterations at a large number otherwise results will not be accurate or these may be worse, [15].

We can analyze the microgrids, whether they are grid-connected or islanding mode, with uncertain energy generators like PV, wind, battery, and fuel cells. Microgrid can be considered as a non-linear, and constrained-based multi-objective optimization problem due to the integration of uncertain energy resources with it. To get stable and reliable energy from microgrids, we can use a non-dominated sorting genetic algorithm as an optimal tool to find the set of solutions for such a problem. There are several types of genetic algorithms that can be used for several types of problems so we can get more accurate results. Non-dominated sorting genetic algorithm is designed for the solution of probabilistic problems. We can use modified non-dominated sorting genetic algorithm for uncertain problems in microgrids and networked microgrids in both cases of islanded mode and grid-connected mode of operation, [16].

The trade-off in renewable energy resource integration, cost, and reliable power can be adjusted by sizing methodology considering all the above three variables for a multi-objective optimization problem. For this purpose, we can use a multi-objective genetic algorithm to find the optimal values set of renewable energy resource integration, cost, and reliability by selecting suitable topology and size. The non-dominated sorting genetic algorithm can give accurate results in case of trade-off problems for renewable energy resources and their integration into the power system. It has the property of exploring the search space efficiently. The cost function, renewable energy resources integration, and reliability of the power system are optimized using a non-dominated sorting genetic algorithm, [17].

We have introduced a multi-objective genetic algorithm (MOGA) in order to solve the multi-objective optimization problem. Genetic algorithms, being meta-heuristic techniques, are used to solve complex optimization problems. These are inspired by natural selection and based on the survival of the fittest. In this FTOP, we have applied a multi-objective genetic algorithm in which the initial population is created randomly. For each iteration, we have performed a crossover on the genes for gene recombination (one-point crossover). The mutation is performed in each gene in order to calculate the objective function showing the population obtained and the existing population. Meanwhile, the algorithm selects and transfers a gene having a lower objective function to the next iteration. The iterations go on until we have reached an optimal value of outcomes as shown in the genetic algorithm flowchart in Figure 1.

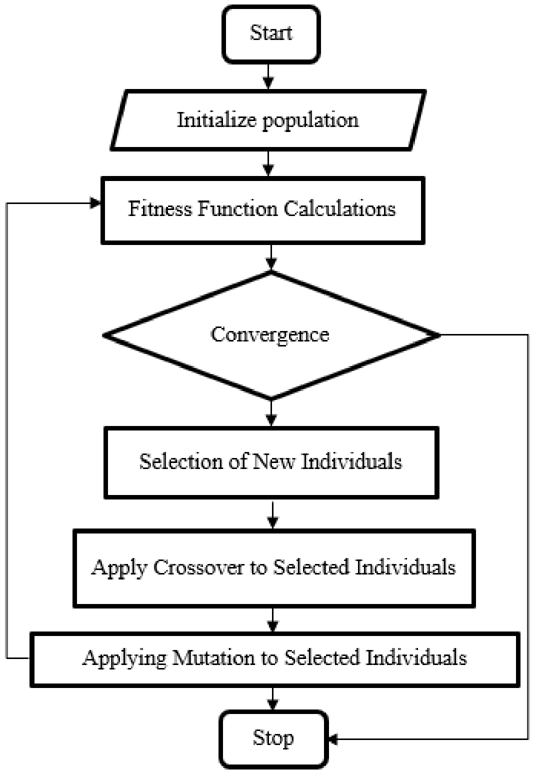

Fig. 1: Flow chart for Genetic Algorithm, [18]

4 Results and Discussions

In order to show the performance of the proposed formulation, we have considered three networked microgrid configurations (Figure 2) for the simulations and their results.

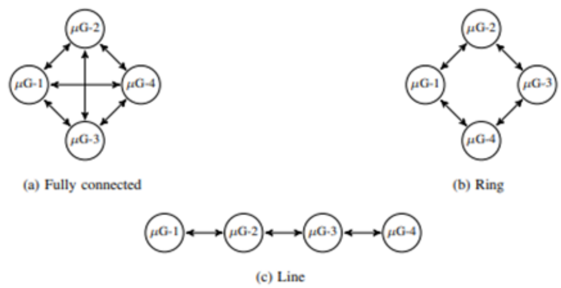

Fig. 2: Three networked configurations of microgrids

4.1 Line Configuration (*microgrid N° 4 in failure*)

In line configuration, the Lagrange multiplier values and energy values with the Heuristic algorithm and without it (approach presented in [19]) are shown in Table 1. Energy sales and energy generated are shown in Table 2. Please note this is the normal operation without considering failures in any microgrid. Table 1, Table 2, Table 3 and Table 4 are the results shown in line configuration without any microgrid failure in networked microgrids.

In Table 5, The energy sell and and energy generation of each microgrid in a networked microgrid by using a heuristic algorithm.

The total energy cost occurred in all four networked microgrids with and without the heuristic algorithm is shown in Table 3. Each microgrid has improved the total energy cost by using a heuristic algorithm.

In Table 6, we have obtained the total energy cost in USD/hour of the networked microgrids system. We can see the improvement in the duality gap in case of using a heuristic approach.

If we have considered a failure in microgrid 4 in-line configuration, and that the network must continue operating, we solve the problem formulation in equation (3), resulting in the following results from Table 7, Table 8, Table 9, Table 10, Table 11, Table 12, Table 13 and Table 14.

Table 3. Lagrange multipliers and Energy values

LAMBDAS (HEURISTIC)				LAMBDAS			
98.66	98.02	82.75	59.31	102.6	98.00	82.73	59.3
E_min (HEURISTICO)				E_min			
0	0	0	0	0	0	0	0
1.023	0	0	0	1.024	0	0	0
0	2.073	0	0	0	2.073	0	0
0	0	3.181	0	0	0	3.181	0

Table 4. Energy sales and generation of each microgrid

E_sell (HEURISTIC)	E_sell
0	0
1.02399	1.02403
2.07386	2.07366
3.18159	3.18109
E_gen (HEURISTIC)	E_gen
9.97601	9.97597
9.95012	9.95037
9.89228	9.89257
4.18159	4.18109

Table 5. Total energy cost per microgrid

Total energy cost per microgrid (HEURISTIC)			Total energy cost per microgrid		
Gen.	Trans.	Total	Gen.	Trans.	Total
686.779	3.8616	690.64	686.774	3.86192	690.636
684.146	15.8394	699.985	684.17	15.8363	700.006
678.935	37.2792	716.214	678.959	37.2676	716.226
328.655	0	328.655	328.626	0	328.626

Table 6. The total energy cost and duality gap

Total Energy Cost (Heuristics) USD/hour	Total Energy Cost USD/hour	Final Duality Gap (Heuristic)	Final Duality Gap
2435.494341 (2435.494253)	2435.494314 (2435.494313)	-0.802124	-0.031997

Table 7. Lambdas values and E_min of all 4 microgrids in line configuration

Lambdas			
82.5756	88.8685	80.3659	60.4385
E_min			
0	0.854367	0	0
1.05437	0	0	0
0	1.15437	0	0
0	0	2.70548	0

Table 8. E_sell and E_gen values of all 4 microgrids in line configuration

E_sell		E_gen	E_c
0.854367	0	10.8	11
1.05437	0.925677	10.0456	11
1.15437	1.58809	9.44889	11
2.70548	4.89882	3.70548	1

Table 9. Total energy cost per microgrid in networked microgrids

Generation	Transmission	Total
1031.32	4.09413	1035.42
694.923	7.59579	702.519
650.173	26.9566	677.13
300.491	0	300.491

Table 10. The total energy cost and duality gap

Total energy cost	Final duality gap
2715.555782(2427.593190) USD per hour	-85.432276

Table 11. E_gen (fault tolerant case) and E_gen (Heuristic)

E_gen (fault tolerant case)	E_gen (Heuristic)
10.8000	9.97601
10.0456	9.95012
9.4489	9.89228
3.7055	4.18159

Table 12. E_gen (Heuristic) in other three microgrids in contigency

E_gen	9.9760	10.9745	12.0495

Table 13. The operation (fault tolerant) in the other three microgrids in contingency

E_gen	10.8000	11.1000	11.1000

Table 14. The capacity out

Capacity Out	0.0800	0.1100	0.1100

Please note that the operating cost increased from 2435.494341 to 2715.555782 USD per hour, but the scheduling of the microgrids is more conservative. This means that if we operate the system in the case E_gen (HEURISTIC), in contingency (microgrid 4 in failure), we will have the following operation in the other three microgrids (solution of formulation in equation (6)).

In this case, Table 10, microgrid 3 exceeds the capacity (we set the capacity in the Pmax (10 MW) plus a delta of 1.1), in this way this operating point is not factible.

If we operate the system in the conservative case fault-tolerant optimization, in contingency (microgrid 4 in failure), we will have the following operation in the other three microgrids (solution of formulation in equation (6)) shown in Table 11. In Table 12, values mean that we are not superating the capacity.

4.2 Ring Configuration *(microgrid N° 4 in failure)*

In Ring configuration, the lagrange multiplier values and energy values with the Heuristic algorithm and without it are shown in Table 15. While energy sales and energy generated are shown in Table 16. Please note this is the normal operation without considering failures in any microgrid. Table 17, Table 18, Table 19 and Table 20 are the results shown in ring configuration without any microgrid failure in networked microgrids.

Table 15. Lagrange multipliers and Energy values

LAMBDAS (HEURISTIC)			
72.1621	73.3853	72.1621	59.4825
E_min (HEURISTICO)			
0	0.567439	0	0
0	0	0	0
0	0.567439	0	0
1.72146	0	1.72146	0

In Table 21, The energy sell and and energy generation of each microgrid in a networked microgrid by using a heuristic algorithm.

The total energy cost occurred in all four networked microgrids with and without the heuristic algorithm is shown in Table 22. Each microgrid has improved the total energy cost by using a heuristic algorithm.

Table 16. The energy sell and generation of each microgrid

Generation	Transmission	Total
677.911	16.9724	694.883
618.795	7.75604	626.551
677.83	16.9805	694.81
395.04	0	395.04

Table 17. The total energy cost per microgrid

Total energy cost per microgrid (HEURISTIC)		
Generation	Transmission	Total
675.356	10.9137	686.269
676.777	2.37163	679.148
675.355	10.9138	686.269
344.178	0	344.178

In Table 23, we have obtained the total energy cost in USD/hour of the networked microgrids system. We can see the improvement in the duality gap in the case of using a heuristic approach.

Table 18. The total energy cost and duality gap

Total Energy Cost (Heuristics) USD/hour	Final Duality Gap (Heuristic)
2395.864618 (2395.864618)	-0.027222

If we have considered a failure in the microgrid 4 in ring configuration, and that the network must continue operating, we solve the problem formulation in equation (3), resulting in Table 19, Table 20, Table 21, Table 22, Table 23, Table 24, Table 25 and Table 26.

Table 19. Lambdas values and E_min of all 4 microgrids in line configuration

Lambdas			
75.1912	82.7514	75.1950	59.379
E_min			
0	1.02642	0	0
0	0	0	0
0	1.02591	0	0
2.14676	0	2.14726	0

Table 20. E_sell and E_gen values of all 4 microgrids in ring configuration

E_sell	E_gen	E_c
1.02642	9.87966	11
0	8.94768	11
1.02591	9.87864	11
4.29402	5.29402	1

Table 21. Total energy cost per microgrid in networked microgrids

E_sell (HEURISTIC)
0.567439
0
0.756792
3.44293
E_gen (HEURISTIC)
9.84598
9.86512
9.84597
4.44293

Table 22. The total energy cost and duality gap

Total energy cost	Final duality gap
2411.284416 (2392.840878) USD per hour	-15.445709

Please note that the operating cost increased from 2395.864618 to 2411.284416 USD per hour, but the scheduling of the microgrids is more conservative.

Table 23. E_gen (fault tolerant case) and E_gen (Heuristic)

E_gen (fault tolerant case)	E_gen (Heuristic)
9.87966	9.84598
8.94768	9.86512
9.87864	9.84597
5.29402	4.44293

This means that if we operate the system in the case E_gen (HEURISTIC), in contingency (microgrid 4 in failure), we will have the following operation in the other three microgrids (solution of formulation in equation (6)).

Table 24. E_gen (Heuristic) in the other three microgrids in contigency

E_gen	10.4552	12.0897	10.4552

In this case Table 24, the microgrid 2 exceed the capacity (we set the capacity in the Pmax (10 MW) plus a delta of 1.1), in this way this operating point is not factible.

If we operate the system in the conservative case fault-tolerant optimization, in contingency (microgrid 4 in failure), we will have the following operation in the other three microgrids (solution of formulation in equation (6)) shown in Table 25.

Table 25. The operation (fault tolerant) in the other three microgrids in contingency

E_gen	10.9503	11.1000	10.9497

In Table 26, the values means that we are not superating the capacity.

Table 26. The capacity out

Capacity Out	0.0950	0.1100	0.0950

4.3 Full Configuration (*microgrid N° 4 in failure*)

In Full configuration, the lagrange multiplier values and energy values with the Heuristic algorithm are shown in Table 27. While energy sales and energy generated are shown in Table 28.

Please note this is the normal operation without considering failures in any microgrid. Table 29, Table 30 and Table 31 are the results shown in full configuration without any microgrid failure in networked microgrids.

Table 27. The Lagrange multipliers and Energy values

LAMBDAS (HEURISTIC)			
68.1869	68.1908	68.1907	59.5474
E_min (HEURISTICO)			
0	5.38264e-06	0	0
0	0	0	0
8.80918e-06	1.41918e-05	0	0
1.17347	1.17348	1.17346	0

Table 28. The energy sales and generation of each microgrid

E_sell (HEURISTIC)	
5.38264e-06	0.000266166
0	0.000282511
2.3001e-05	0.000248226
3.52041	3.54223
E_gen (HEURISTIC)	
9.82653	11
9.82653	11
9.82656	11
4.52041	1

In Table 28, The energy sell and energy generation of each microgrid in a networked microgrid by using a heuristic algorithm.

The total energy cost occurred in all four networked microgrids with and without the heuristic algorithm is shown in Table 29. Each microgrid has improved the total energy cost by using a heuristic algorithm.

In Table 30, we have obtained the total energy cost in USD/hour of the networked microgrids system. We can see the improvement in the duality gap in the case of using a heuristic approach.

Table 29. The total energy cost per microgrid

Total energy cost per microgrid (HEURISTIC)		
Generation	Transmission	Total
673.992	5.07133	679.063
673.99	5.07138	679.061
673.994	5.07126	679.065
348.788	0	348.788

Table 30. The total energy cost and duality gap

Total Energy Cost (Heuristics) USD/hour	Final Duality Gap (Heuristic)
2385.977873 (2385.977697)	-1.351708

If we have considered a failure in the microgrid 4 in full configuration, and that the network must continue operating, we solve the problem formulation in equation (3). It is something interesting in this case, the schedule of the generation is the same that in the previous case since the full configuration is robust under contingency.

This means that if we operate the system in the case E_gen (HEURISTIC), in contingency (microgrid 4 in failure), we will have the following operation in the other three microgrids (solution of formulation in equation (6)).

Table 31. E_gen (Heuristic) in the other three microgrids in contigency

E_gen	11	11	11

In this case Table 31, there is no capacity overhaul (we set the capacity in the Pmax (10 MW) plus a delta of 1.1), in this way the operating point is factible.

5 Conclusions

The fault-tolerant optimization in microgrids is an integral factor of research due to the uncertainty of renewable energy resources. Stable and reliable energy availability is the key purpose of fault-tolerant optimization in this work, and results show that we have minimized the total cost of the system and consistent supply of energy even for the failure of a microgrid in the networked microgrids. We have used genetic algorithms in order to optimize and control fault tolerance in networked microgrids' operation. We have used multi-objective genetic algorithm (MOGA) for solving FTOP. A fault-tolerant optimization problem (FTOP) has the possibility of partial components of the system failing or generating errors during the operation. We have determined the best possible solution which is obtained even in the presence of failure or errors in networked microgrids. We have minimized the total cost of the system and provision of a consistent supply of energy even for the failure of a microgrid in the networked microgrids to get stable and reliable energy. FTOP problems mostly occur in critical and uncertain systems like microgrids in which reliable power is the demand from the customers with continuous availability. We will combine this problem with load balancing and solve it by using advanced artificial intelligence algorithms as future work.

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