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Optimal Operation of a Distributed Generation Microgrid based on the Multi-Objective Genetic Algorithms.

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Abstract. This document describes the application of multi-objective genetic algorithms as techniques and tools to optimize generation and distribution in small microgrids. In this way, genetic algorithms have been used for the allocation of distributed generation to reduce losses and improve the voltage profile. The IEEE14 network has been taken as a study and analysis model. This smart grid has 14 nodes and integrates several generation units, both conventional and renewable, transformers, and multiple loads. In this way, a multi-objective metaheuristic algorithm is proposed with the purpose of planning the power distribution grid based on a series of conditions such as the optimal generation configuration, the minimization of power losses in the lines, power transfer capacity, the reduction of CO_2 emissions, and the optimization of the benefits obtained in renewable generation. The overall purpose is the development of an intelligent microgrid management system that is capable of determining the optimal configuration, by estimating demand, energy costs, and operating costs.

Keywords. Power flow solver, Optimal DG allocation, Local energy market, Genetic algorithm, Distributed optimal power flow, Optimization algorithm, Agent-based modelling and simulation, Dynamic energy management.

1. Introduction

In this last decade, one of the main objectives of the energy sector is the integration of renewable energies in distributed generation systems. Renewable energy sources have experienced great growth, especially wind turbines and photovoltaic panels, so the need has arisen to find a precise method to analyze their impact on power distribution networks [1], [2]. However, small microgrids based on renewable energy, as the only source of power supply, have several associated drawbacks such as randomness and stability.

A microgrid is a small power system that contains distributed generation, energy storage devices, loads, protection devices, and control systems The intermittency and randomness of these renewable energy sources can easily cause fluctuations in the power system, causing a strong negative impact on microgrid stability [3]. Battery energy storage systems (BESS) can suppress these fluctuations in the distributed power supply. Thus, for example, in [4] a hybrid energy storage system is described to stabilize a system based on a wind turbine or photovoltaic panels.

Power optimization in these microgrids is a multiobjective and non-linear optimization problem [5]. It is also possible to include different constraints [6]. As a consequence of the detailed analysis of the impact of renewable energy sources, there is a need to implement new tools that help optimizing these distributed power generation systems [7]. This type of optimization tool has been discussed in the literature by numerous authors [8], [9]. Thus, different methods have been proposed, such as nature inspired techniques [10], [11], hybrid intelligent algorithms [12], society inspired algorithms [13], linear programming [14], robust optimization [15], analytical methods [16], etc.

In this paper, an optimization tool based on genetic algorithms is proposed. Genetic algorithms are often used to optimize complex functions that have different local maxima and minima, and therefore require a large number of iterations to reach the global maximum and minimum of the objective function. For the implementation of the genetic algorithm, the Python language has been used, as well as several of its libraries.

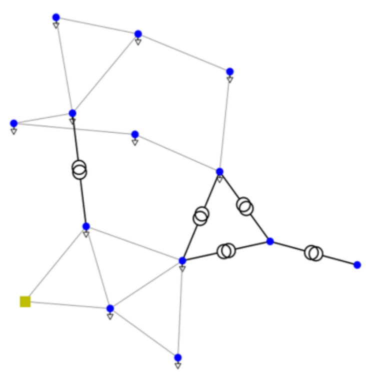

Fig. 1. Representation of the IEEE-14 microgrid.

2. Problem Formulation

Initially, a small microgrid has been proposed, up to 10MW, with 14 nodes (IEEE14 network model) that will use distributed generation, instead of being supplied from the supply network. This microgrid will include several distributed power generation systems (DG) and energy storage units (ST). In microgrids based on distributed generation, the interaction between three agents often takes place [17], the power producer (generally the owner of the power generation units), the network operator, and the consumer. It should be noted that each of these agents has a different interest [18].

In this way, the power producer seeks to maximize its economic benefits through the sale of energy to the network operator. Thus, in order to maximize its economic benefits, the power producer must consider several parameters, such as the contract price of the power generation units, their investment costs, as well as the operating costs required for their installation [19].

Equation (1) describes, in a simplified way, the calculation of the producer's benefits, which is the first objective function that has been considered for the application of the genetic algorithm.

$$B = (C_{PC} + C_{PL}) - CO - CI_{DG} \tag{1}$$

where, B is the benefit obtained by the energy producer (who in turn is the owner of the installation), C_{PC} are the costs derived from the power sale contract prices, C_{PL} are the costs of the power losses produced in the distribution lines, CO is the operating cost of the power generation units, CI_{DG} are the investment costs that the energy producer will have to bear.

Each of these parameters has to be studied and calculated separately. In addition, all these parameters will depend on the power flows in the different power distribution lines. This document analyzes the interest of a single agent, the power producer. Therefore, the first objective function is represented in equation (1). Thus, in this case, the purpose of the genetic algorithm is the maximization of the benefits of the power producer (the agent studied). The three indicators that will be evaluated in the implemented algorithm are the following:

- Optimal location. The solution will have an optimal location for all the DG units to be installed on the microgrid. Both the number of generation units and the node in which they should be located will be determined.
- Optimum size. The size of the installed unit will also be evaluated, with size being understood as the capacity measured in installed power. The installed power will be different depending on the type of unit, whether it is photovoltaic panels, a wind turbine, or a small internal combustion engine.
- Contract Price. This parameter will be calculated through a predetermined price value per generated MWh and evaluating the power demand over a specified period of time.

A. Contract price costs

The benefit that the energy producer obtains from the sale of the MWh depends on the values reached in the prices of the sales contracts (*PC*) that the same producer must establish. Each power generating unit has a different *PC*, depending on the type of DG unit in question. Table I shows the *PC*s considered for the different DG units to be analyzed.

Table I. The contract price of each type of DG unit.

DG unit	***PC (€/MW sold)***
Photovoltaic (PV)	*95*
Wind Turbine (WT)	*90*
Internal Combustion Engine (ICE)	*90*
Battery Energy Storage System (ST)	*95*

In this way, the costs are calculated as the product of the contract price (€/MW) by the MW generated by each type of unit. In equation (2) you can see the value of C_{PC},

$$C_{PC} = \sum_{j=1}^{n} \left(PC \times P_{GEN,j}\right) \tag{2}$$

where, C_{PC} are the costs derived from the power sales contract prices, PC is the energy sale contract price, and $P_{GEN,\,j}$ is the power generated in each DG unit; where $j = \{1,\ 2, \ldots,\ n\}$ represents the number of generator included in the microgrid.

B. Power loss costs

Another parameter that appears in the calculation of the benefits of the power producer is the costs associated with the power losses of the power distribution lines. This economic cost is assumed by the network operator, which is the agent directly linked to the purchase of electricity. The value of these power losses depends, among other factors, on the lengths of the power distribution lines. Therefore, the main objective is to calculate the optimal location of the different power generators within the microgrid. Thus, the costs associated with power losses will be (3),

$$C_{PL} = \sum_{i=1}^{n} \left(c_{PL} \times P_{PL,i}\right) \tag{3}$$

where, C_{PL} is the total cost derived from power losses in the microgrid, $P_{PL,\,i}$ is the value of the power losses (MW) in each of the power distribution lines; where $i = \{1,\ 2, \ldots,\ n\}$ represents the number of power distribution line in the microgrid. While c_{PL} is the unit cost €/MW of power losses per MW. This value of power losses in the different power distribution lines is calculated by the simulation software based on the location of the power generators and the power flows in the different lines. It should also be noted that this value of power losses refers to those that have occurred during the 24 hours (simulation period).

Table II. Investment costs of each type of DG unit.

DG unit	***ci_{PL} (€/MW)***
Photovoltaic (PV)	*1.500.000*
Wind Turbine (WT)	*1.200.000*
Internal Combustion Engine (ICE)	*400.000*
Battery Energy Storage System (ST)	*1.300.00*

C. Investment costs

The investment costs are the costs per installed MW associated with the producer. These production costs depend on the size and type of generator. In this case, it will be assumed that renewable generation is more expensive than conventional generation. The investment costs of the storage units are considered high, see table II. Thus, the investment costs are given in a simplified way by equation (4),

$$CI_{DG} = \sum_{j=1}^{n} \left(ci_{PL} \times P_{INS,j} \right) \tag{4}$$

where, CI_{DG} represents the cost derived from the investment, ci_{PL} is the unit investment cost in €/MW, while $P_{INS,\,j}$ is the installed power inMW; where $j = \{1, 2,\dots, n\}$ represents the number of generator in the microgrid.

It should be noted that the cost per MW installed in the case of the ICE (internal combustion engine) has been set well below the other costs. His reason is that including CO_2 emissions as a second objective function causes the algorithm itself to tend to discard elements with ICE. In the real world, it would be very difficult to implement a microgrid that was only based on renewable energies. For this reason, a balance has been sought between the value of CO_2 emissions and benefits. This assumption is closer to reality. The investment costs are divided over 20 years, which is the amortization period considered to recover the investment. In this case, economic inflation has not been considered.

D. Operating costs

The operating costs are those costs related to the exploitation of the elements of the microgrid. The most frequent costs are associated with fuel and maintenance of the installation. To simplify the calculation of this parameter, it is considered that these costs are proportional to the power generated in the installation.

$$CO = \sum_{j=1}^{n} \left(c_{OP} \times P_{GEN,j} \right) \tag{5}$$

where, CO are the operating costs of the installation, c_{OP} is the unit operating cost per MW generated c_{OP} = 60€/MW, and $P_{GEN,\,j}$ is the power generated in each DG unit; where $j = \{1, 2,\dots, n\}$ represents the number of generator.

E. CO_2 Emissions

A current objective is the integration of renewable energies in microgrids in order to reduce emissions caused by generation using fossil fuels. For this reason, the minimization of the value of CO_2 emissions has been included as the second objective function of the genetic algorithm.

In the case studied here, the emissions can only be produced by the internal combustion generator. In this way, the default algorithm tends to choose individuals that only have renewable generation. The purpose is that the value of emissions is zero. Thus, equation (6) presents the calculation of emissions based on the energy generated at all times.

$$ECO_2 = \sum_{j=1}^{n} \left(f_{EM} \times P_{ICE,j} \right) \tag{6}$$

where, ECO_2 is the total CO_2 emissions generated by the internal combustion engines (kg CO_2), $P_{ICE,\,j}$ is the power generated by each ICE; where $j = \{1, 2,\dots, n\}$ represents the number of generator in the microgrid. While f_{EM} is the unit emissions factor per MWh generated. Indicate that a coefficient f_{EM} = 0,8 kg CO_2/MWh has been considered.

F. Reactive power in the microgrid

The purpose of this objective function is to minimize the power losses in the lines caused by the total reactive power in the microgrid. To do this, the simulation software previously calculates the reactive power in each of the nodes and power flows in the different power distribution lines (7).

$$Q_T = \sum_{i=1}^{n} \sum_{j=1}^{n} Q_{Ni,j} \tag{7}$$

where, Q_T is the total reactive power of the microgrid and $Q_{Ni,\,j}$ is the reactive power corresponding to $node_{i,\,j}$ if $i = j$ or to the distribution $line_{i,\,j}$ if $i \neq j$; where $i = \{1, 2,\dots, n\}$, $j = \{1, 2,\dots, n\}$ represent the different coefficients.

G. Constraints

To solve the multi-objective optimization, it is necessary to consider the microgrid operation restrictions. These constraints indicate the state of operation, the range of the optimization function, the limitations, etc. [6]. Thus, the following restrictions have been considered.

- power balance constraints.

$$\sum_{j=1}^{n} P_{GEN,j} = P_{load} + P_{loss} + P_{ST} \tag{8}$$

- distributed generation power constraints.

$$P_{GEN,j}^{min} \leq P_{GEN,j} \leq P_{GEN,j}^{max} \tag{9}$$

$$P_{ICE}^{min} \leq P_{ICE,j} \leq P_{ICE}^{max} \tag{10}$$

Achieving effective use of storage systems in microgrids is essential due to the high cost of stored energy compared to other conventional sources. In this model, the degradation of the battery and its self-discharge coefficient has not been taken into account. The main restrictions associated with the storage system are described below.

- battery energy storage system constraints.

$$P_{ST}^{min} \leq P_{ST,j} \leq P_{ST}^{max} \tag{11}$$

$$S_{SOC}^{min} \leq S_{SOC,j} \leq S_{SOC,j}^{max} \tag{12}$$

- discharge battery. $\boldsymbol{P_{ST,j}(t) \geq 0}$

$$S_{SOC}(t) = S_{SOC}(t-1) - P_{ST,j}(t)\frac{\Delta t}{\eta_{ST}} \tag{13}$$

- charge battery. $\boldsymbol{P_{ST,j}(t) \leq 0}$

$$S_{SOC}(t) = S_{SOC}(t-1) - P_{ST,j}(t)\frac{\Delta t}{\eta_{ST}} \tag{14}$$

where, $\boldsymbol{P_{load}}$ is the total power demanded, $\boldsymbol{P_{loss}}$ are the power losses in the microgrid, $\boldsymbol{P_{GEN}^{min}}$ and $\boldsymbol{P_{GEN}^{max}}$ are the lower and upper power limits in the generation units. While $\boldsymbol{P_{ST}^{min}}$ and $\boldsymbol{P_{ST}^{max}}$ are the lower and upper power limits of the energy storage system, $\boldsymbol{\eta_{ST}}$ is the performance of the charge-discharge process of the storage system, $\boldsymbol{S_{SOC}^{min}}$ and $\boldsymbol{S_{SOC}^{max}}$ are the lower and upper limits of the state of charge of the battery.

3. Codification methodology proposed

To study a microgrid by means of a genetic algorithm, it is necessary to carry out a coding, structuring its data in a chromosomal way. Thus, each element (individual) has been defined as a vector formed by "1" and "0". The range of the vector is given by the number of nodes that make up the utility grid. In the analyzed case (IEEE-14 network) the vector is made up of 14 nodes and each value (0 or 1) is chosen randomly.

Thus, if a box takes the value "0", it means that there is no generation in that node. If, on the other hand, the box takes the value "1", it means that a power generator or an energy storage unit is added to that node, see Fig. 2. In this case, the genetic algorithm chooses the microgrid configuration that represents the most benefits for the power producer.

0	1	2	3	4	5	6	7	8	9	10	11	12	13
1	0	1	0	0	1	0	1	0	1	0	0	0	1

Fig. 2. Example of vector encoded in the microgrid.

Likewise, Table III shows the capacity of the generation units. This capacity value is optimized by the genetic algorithm when assigning a generation unit to a node.

Table III. Generation unit capacity.

Unity	P_{GEN}^{max}	P_{GEN}^{min}	Q_{GEN}^{max}
Photovoltaic Panels	4MW	0MW	±1MVAr
Wind Turbine	2MW	0MW	±1MVAr
Internal Combustion Engine	8MW	0MW	±1MVAr
Energy Storage System	2MW	0MW	±2MVAr

4. Optimization Genetic Algorithm

For the definition of the genetic algorithm, the DEAP library included in the Python programming software has been used. The function that executes the genetic algorithm needs two input parameters, the population and the number of generations, which translate into the number of iterations that it will carry out, see Fig. 3.

```python
#AG is defined
def main(poblacion, generacion):
    random.seed(64)

    #Creating individual population
    pop = toolbox.population(n=poblacion)

    #CXPB is the probability with which two individuals are crossed
    #MUTPB is the mutation probability of an individual
    CXPB, MUTPB = 0.5, 0.2

    print("Beginning of evolution")

    #Evaluating the entire population
    fitnesses = list(map(evaluate, pop))

    #Assigning each individual their fitness
    for ind, fit in zip(pop, fitnesses):
        ind.fitness.values = fit

    print("Evaluated individuals %i" % len(pop))

    #A list of the fitness values from all individuals in the population is drawn
    fits1 = [ind.fitness.values[0] for ind in pop]
    fits2 = [ind.fitness.values[1] for ind in pop]
    fits3 = [ind.fitness.values[2] for ind in pop]

    #The variable that will record the number of generations is defined
    g = 0
```

Fig. 3. Genetic algorithm programming using Python language.

Two coefficients are also introduced that are used in the genetic operators and that represent the crossover probabilities of the individuals (CXPB) and the mutation in one of them (MUTPB). Figure 3 shows the code where the configuration of both parameters appears in the algorithm. In addition, 3 variables are defined to store the values of the objective functions in the different individuals. Subsequently, the constraints of the genetic algorithm are indicated, as well as the different conditions for the loop to continue executing until any of them is not met.

Once the evolution loop has started, the genetic operators are applied to the population, selection, cloning, mutation, with the previously defined probability constants, see Fig. 4. After applying the operators, the individuals are evaluated and the values of the objective functions are saved. Likewise, the data and information of the best individuals of each generation are stored and the population is replaced by the new offspring obtained.

```python
#Selecting the new population for the new generation
offspring = toolbox.select(pop, len(pop))

#Cloning selected individuals
offspring = list(map(toolbox.clone, offspring))

#Applying crossover and mutation in the offspring
for child1, child2 in zip(offspring[::2], offspring[1::2]):

    #Two individuals are crossed with probability CXPB
    if random.random() < CXPB:
        toolbox.mate(child1, child2)

        #Fitness value of children
        #will be recalculated later
        del child1.fitness.values
        del child2.fitness.values

for mutant in offspring:

    #Two individuals with MUTPB probability are mutated
    if random.random() < MUTPB:
        toolbox.mutate(mutant)
        del mutant.fitness.values
```

Fig. 4. Application of the different genetic operators on the proposed algorithm.

As a solution, the algorithm returns the different values corresponding to the objective functions and the optimal location of the distributed generators in the microgrid.

5. Simulation Results

Next, the simulation results obtained during the implementation of the genetic algorithm are presented. The optimal solution is presented, analyzing the impact of renewable energy within the microgrid and how its value affects the objective function. In this way, the simulation of the optimal microgrid for a period of 24 hours is shown, at the same time that the simulation results obtained are represented. The configuration of the optimal microgrid, obtained as a result of the application of the genetic algorithm, which includes the location and type of generator in the different nodes, is shown in Table IV.

Table IV. Optimal configuration of the microgrid; Wind Turbine (WT), Photovoltaic panels (PV), Internal Combustion Engine (ICE), and Battery Energy Storage System (ST).

Node	***0***	***1***	***2***	***3***	***4***	***5***	***6***
	1	*1*	*0*	*1*	*1*	*1*	*1*
Type	*ICE*	*WT*	*---*	*ST*	*PV*	*PV*	*ICE*
Node	***7***	***8***	***9***	***10***	***11***	***12***	***13***
	0	*1*	*1*	*1*	*1*	*1*	*0*
Type	*ICE*	*---*	*ST*	*ST*	*PV*	*WT*	*---*

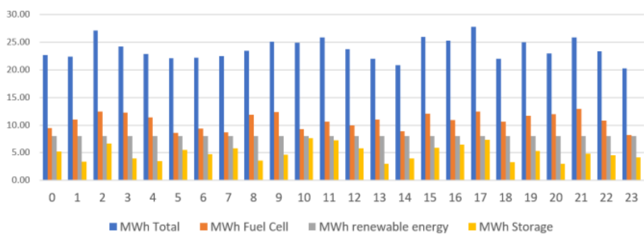

Fig. 5. Diagram with the power generated in the optimal microgrid 24 hours a day.

Meanwhile, Fig. 5 shows the generation of total power in the microgrid studied during a period of 24 hours. This power generation (MWh-total) has been divided into 3 types: MWh-ICE, MWh-renewable (WT+PV), and MWh-ST. The average power values per node for the optimal microgrid have also been calculated.

At the same time, Fig. 6 indicates the nodes that provide energy to the microgrid and those nodes that demand power. Those nodes where there are no loads, there are only energy storage type units, can have negative power if they deliver power to the microgrid or, conversely, positive power if they absorb power from the microgrid. In the rest of the nodes, the loads demand more power than that generated by the power generators from renewable sources, due to their capacity. In this way, the ICE units are activated.

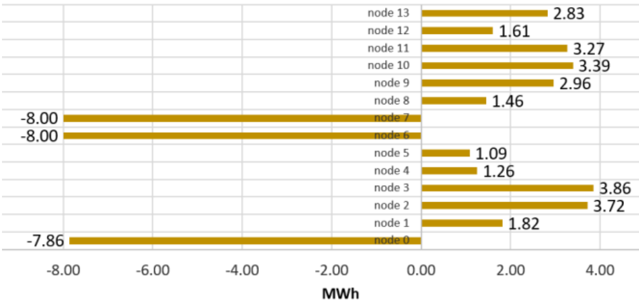

Fig. 6. Average power flow per node in the microgrid.

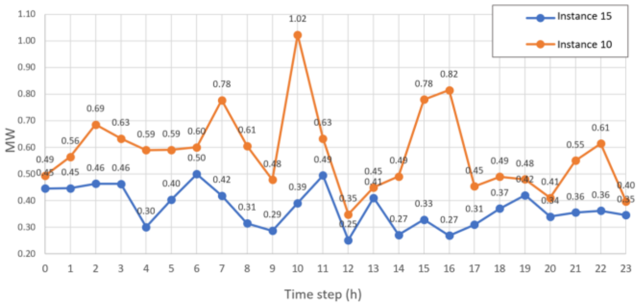

Fig. 7. Comparison of power losses in the microgrid.

In Fig. 7 you can see the results obtained in the power losses of the microgrid (third objective function) depending on the number of elements that have been selected in the genetic algorithm. The minimization of reactive power in the microgrid is an effective resource to control the value of power losses and therefore to calculate the optimal solution. Power losses in power distribution lines are caused by different factors such as the length of the line, the type of conductor and its configuration, the imbalance of reactive power flows, etc.

6. Impact of Renewable Energies

Another concept to analyze is the integration of renewable energies in the microgrid. For this, different scenarios will be studied. In all the cases studied, energy storage units are available.

- scenario#1: without renewable energies.
- scenario#2: with renewable energies.
- scenario#3: only renewables energies.

Once the genetic algorithm has been applied, the following results have been obtained, see table V.

Table V. Comparison of simulation results. Data obtained in the different scenarios.

scenarios	Benefits (M€/year)	Emissions (tons CO_2/year)
without renewables	105.1970	478.5616
with renewables	82.4521	303.2321
only renewables	18.9188	0
photovoltaic (PV)	15.8140	0
wind-turbine (WT)	8.6685	0

As can be seen in the table, a network made up of internal combustion engines (ICE) and battery energy storage systems (BESS) increases the benefits. This is because the investment cost is lower than that made up of wind units (WT) or photovoltaic panels (PV). Likewise, as a consequence of the use of these power generation units, the value of emissions (kg CO_2/year) has also increased. On the other hand, if microgrids composed of renewable energy sources and storage units are studied, it is concluded that it is more beneficial to integrate several types of power generators in the installation to combine capacities, investment costs, and power sales prices.

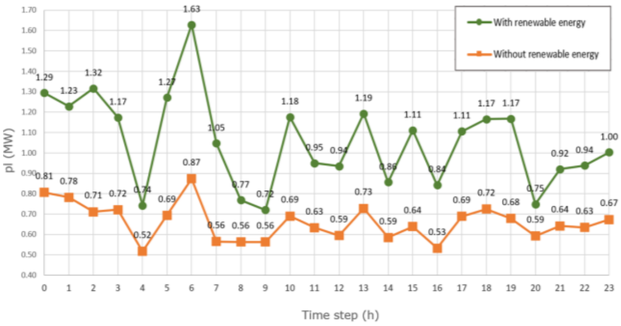

Fig. 8. Comparison of power losses in distribution lines in the IEEE-14 microgrid.

On the other hand, Fig. 8 presents the power losses in the microgrid considering some of the study scenarios described. Indicate that by configuring the genetic algorithm so that it only incorporates power generation through units based on fossil fuels, and considering the minimum CO_2 emissions, the algorithm configures a microgrid with a high number of energy storage units.

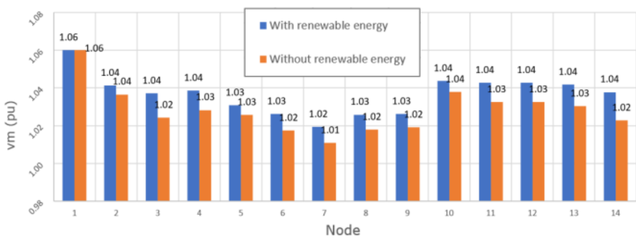

Fig. 9. Average voltage in the different nodes of the microgrid.

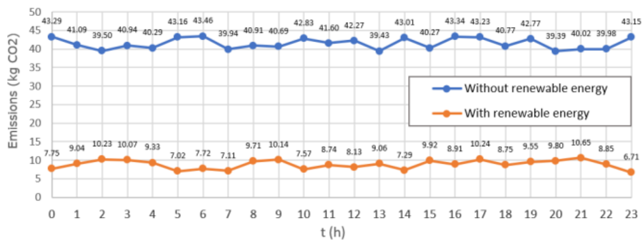

Fig. 10. CO_2 Emissions (kg CO_2).

The integration of renewable energy sources also has an impact on the voltage of the microgrid nodes. Fig. 9 shows the different voltages in each of the nodes of the microgrid. In this case, the node voltages are higher for the microgrid that does not integrate renewable energy sources. Logically, it can be seen that emissions are significantly lower in the case of generator units with renewable sources, since the number of DG-ICE will be much lower, see Fig. 10.

7. Conclusions

In this document, the implementation of a genetic algorithm has been presented with the purpose of optimizing a microgrid of small size and capacity. This optimization process has been based on 3 aspects: the location, the size, and the optimal contract price of each power generation unit (DG). Several Python tools and libraries have been used for its implementation. It has also been found that these genetic algorithms (GA) perform worse with a low number of iterations. Always keeping in mind that if the number of iterations is insufficient, it is very possible that the GA provides a local maximum/minimum as a result of the optimization process. Although a high increase in the number of iterations brings with it an increase in the problem resolution time. Another aspect that affects the efficiency of the algorithm is the weights of the objective functions. In this case, the point of view of the power producer has been considered. Likewise, the analysis carried out could also be developed depending on the network operator or the energy consumer itself.

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