Multiobjective optimization of smart grids considering market power

J Garcia-Guarin¹, S Rivera¹, and L Trigos²
¹ Grupo de Investigación en Compatibilidad Electromagnética, Universidad Nacional de Colombia, Bogotá, Colombia
² Grupo de Investigación en Geotecnia y Medio ambiente, Universidad Francisco de Paula Santander Seccional Ocaña, Colombia

E-mail: pjgarciaq@unal.edu.co, srriverar@unal.edu.co

Abstract. Smart grids gain acceptance for promoting the efficient use of energy resources, based on market prices. These include energy storage systems and electric vehicles; in terms of operation they are complex for controlling the loading/unloading of energy or the buy/sell of it. These networks also encourage demand response programs, that is, according to the price, the users decide how much energy they consume. In addition to promoting the use of renewable energy. This research presents two contributions: 1) The implementation of market power indicators to a mathematical model of smart microgrid and 2) The implementation of a new multiobjective hybrid algorithm called “variable neighborhood search: the differential evolutionary particle swarm”. The results are close to the Pareto front with a uniform distribution. Then, the smart microgrid is evaluated with two restrictions: the Herfindahl-Hirschman index and the three biggest bidders’ index, the first contribution allows no bidder to exercise market power during the 24 hours, which guarantees a competitive electricity market. The second contribution consists in converting this single objective algorithm to a multiobjective version. The performance of the new multiobjective algorithm is verified with the test problems showing good performance.

1. Introduction
Smart grids (SGs) are made up of microgrids which operate independently and are self-sufficient [1]. They share information and can provide benefits for all stakeholders [2]. Some SGs consider aggregators, in fact, they aim at the efficient use of resources [3]. In traditional networks, it is considered that energy goes directly from generators to users [4], while in SGs the flow of information is bidirectional, that is, aggregators can use their own resources (electric vehicles and storage systems) for loading/unloading and buying/selling energy [3]. In terms of operation, variables such as market prices and energy capacity in each node limit the functions of the aggregator.

Demand is essential in electric power systems; it defines the amount that generators and external sources must supply to the network. Demand response programs allow to improve efficiency and avoid energy congestion on the lines [2]. These programs allow consumers to have signals of market prices, based on these signals, consumption is programmed. In smart homes, the aggregator has the ability to program user consumption [1]. This research suggests a mathematical model that prevents the demand from being zero to guarantee the social welfare of the demand. This is a measure of comfort of the users of the energy service.
Traditional generators can offer a firm generation, while with the use of renewable energy such as solar energy, the continuous power supply is guaranteed during the day [5]. SGs can add a greater number of generators which are electric vehicles and storage systems. They are prosumers, that is, they buy / sell energy depending on the period. Electric vehicles have variability in terms of the energy, they can supply to the network because the charge / discharge depends on travel planning.

The electricity market allows transfers of both purchase and sale of energy, this is scheduled for a period of 24 hours [6]. In other words, planning is carried out the day before, on the day of operation, demand forecasts with low accuracy generate economic losses due to excess generation and network overloads. Finally, market price volatility makes network operation difficult.

Artificial intelligence is used for cases of complexity, for this proposal the winning algorithm called “variable neighborhood search - differential evolutionary particle swarm” (VNS-DEEPSO). It is used IEEE Congress on Evolutionary Computation / The Genetic and Evolutionary Computation Conference (IEEE-CEC / GECCO 2019) and it also wins the IEEE World Congress on Computational Intelligence (WCCI 2018) [3-5]. Some qualities such as self-adaptive, evolutionary and learning abilities have made these methods popular. Another advantage that these types of algorithms bring is that not much network information is required, they can operate with black box systems [3]. In addition, the following contributions are presented in this proposal:

- The implementation of the Herfindahl-Hirschman index that measures market concentration and competition between participating markets. Also, the implementation of the index of the 3 largest bidders establishes, one of the three largest generators is essential to meet demand. In literature, these indicators have been proposed to monitor the behavior of generators [7]. As a monitoring tool, they are not sufficient, so this research is used as a restriction to mitigate market power.
- The combined VNS-DEEPSO hybrid algorithm in 2018 has been the best for the competitions in which it has participated [5]. So, in this proposal a methodology is presented which is based on Pareto fronts that allow proximity and distribution to the Pareto front. The new multiobjective algorithm is evaluated with the test functions SCH, CONS, ZDT2 and FON obtaining good results.

Given the context, the presented document has the following structure: in section 2 a summary of the state of the art is made, after that, in section 3 the mathematical formulation and the strategies to turn the hybrid algorithm into a multiobjective algorithm are presented, in section 4 the results are presented and we finish in section 5 with the conclusions.

2. State of the art
Models of electric price market have been implemented and they are presented in Table 1 [8-11]. Abrishambaf’s model encourages the participation of users in the electricity market, rates are assigned according to demand response programs. The mathematical model proposes part of a competitive market in which there is no way to monitor the need for an agent to generate energy [8]. The Quashee’s model has agents called market players, to control prices they propose to maintain an energy reserve which is expensive, so they pose a balance between minimizing costs and making the reservation. They have a distribution system operator that it has the function of managing distributed electrical resources [9].

Pandya's model is made up of 66 distributed sources, 10 external energy sources, one wind unit, 15 storages, 1800 electric vehicles and 32 loads with demand response. However, it lacks a study of the participation of agents for periods based on market power, that is, if an agent changes its position, it causes failures, indeed, they are either overloads or lack of supply [10]. The main contribution in the formulation of the heuristic algorithm that modifies the initial population, however its more advanced version enhanced velocity differential evolutionary particle swarm optimization has greater with a 7% error to the VNS-DEEPSO algorithm, the latter turns out to be better [5]. The 2018 Lezama’s model includes sources of uncertainty for trips with electric vehicles, climatic changes, market price variation
and demand forecast. However, it lacks a mechanism that ensures the well-being of users. The electricity markets are composed of a local and a global market. Carry out a systematic adjustment of the hybrid diagnostic engine (HyDE) algorithm “DE / rand / 1” [11], this algorithm has an average lower than VNS-DEEPSO by 278.9% [12].

The proposed model has in common with the previously presented models of literature on the use of energy resources, storage systems (electric vehicles also fulfill the function of storing energy), use of renewable energy and loads in response to demand. Developed in environments with uncertainty according to [11] and it has the following improvements with respect to the models presented in Table 1:

- Continuous monitoring of the behavior of generators in the electricity market. It is also considered to use restrictions to prevent an agent from having the opportunity to take advantage of technical network failures [8].
- Because the stability of the network does not depend on the energy reserve of the same aggregator, it can use the resources connected to the network as electric vehicles as its own, proving to be an economical solution [9].
- The participation of market agents is established for each period, which guarantees continuous supply for 24 hours [10].
- The VNS-DEEPSO algorithm is compared with other algorithms for the same case studies showing better results in single objective problems [5-12].
- It has a mathematical model for the well-being of the demand that guarantees a minimum energy load for a period of 24 hours [11].

Table 1. Market power.

| No | HHI | RSI3 | 2 Objectives | Markets | Reference |
|----|-----|------|--------------|---------|-----------|
| 1  | No  | No   | No           | Yes     | [8]       |
| 2  | No  | No   | No           | Si      | Yes       |
| 3  | No  | No   | No           | Yes     | [10]      |
| 4  | No  | No   | No           | Yes     | [11]      |
| Author's proposal | Yes | Yes | Yes | Yes | |

3. Mathematical formulation

The mathematical model is made up in two fundamental parts (Figure 1): the first is to take a black box model, which was prepared for the IEEE-CEC / GECCO 2019 and the second to measure the minimum level of welfare of users in response to the demand, the models are improved with restrictions that measure the concentration of agents and the essential that they can be an agent for the intelligent network. Also, the problem is limited with a maximum number of 50,000 evaluations of the objective function [3].

Figure 1. Structure of the problem to solve.

3.1. Profits of smart microgrid

The profits of the microgrid is obtained by subtracting operational costs less revenue as shown in Equation (1) [3].

\[
\text{minimize } Z = \text{OC} - \text{In}
\]  

(1)
3.2. Demand welfare
The welfare of the demand is guaranteed once it is fulfilled once the limit of the minimum amount of energy is reached. According to the literature for first-order control systems the limit is in the stability region [13]. Equation (2) shows the demand cut-off value and this period is calculated as 10% of the maximum power value for all periods.

\[
\text{maximize } J = 1 - e^{-\frac{10 \left( \sum_{t=1}^{T} \sum_{k=1}^{N_k} p_{\text{curt}(t,k)} c_{\text{curt}(t)} \right)}{\max \left( \sum_{t=1}^{T} \sum_{k=1}^{N_k} p_{\text{curt}(t,k)} c_{\text{curt}(t)} \right)}}
\]  

3.3. Restrictions on market power
The purchase / sale of energy is carried out in an auction scheme. This information substantially modifies the purchase / sale prices, in these dynamics the generators may become indispensable and may also seek to increase their income which affects the optimal operation of the network, to mitigate these situations the following is presented measure of two market power incisors.

3.3.1. Herfindahl-hirschman index. The Herfindahl-Hirschman Index (HHI) measures the concentration of the market in a range of 0 to 10,000. When the value approaches 10,000, the market approaches a monopoly, for values close to zero the market has a high level of competition and a 2500 value is considered adequate in competitive markets [7]. Storage systems and electric vehicles act as prosumers, that is, they will only be taken as generators when their value is less than zero according to Equation (3) and Equation (4).

\[
\sum_{e=1}^{N_e} P_{E\text{SS}}(e,t,s) \cdot C_{E\text{SS}}(e,t) > 0
\]

\[
\sum_{v=1}^{N_v} P_{E\text{V}}(v,t,s) \cdot C_{E\text{V}}(v,t) \cdot \pi(s) > 0
\]

The HHI index is calculated as the sum of the square of each competitor divided into the total squared generation. The total generation is calculated by adding each of the generating plants Equation (5). The HHI shown in Equation (6) is only for one period, that is, the HHI restriction <2500 for each 24-hour period must be met.

\[
\text{Gen} = \sum_{e=1}^{N_e} P_{E\text{SS}}(e,t,s) \cdot C_{E\text{SS}}(e,t) \cdot \pi(s) + \sum_{v=1}^{N_v} P_{E\text{V}}(v,t,s) \cdot C_{E\text{V}}(v,t) \cdot \pi(s) + \cdots \\
\cdots \sum_{j=1}^{N_{\text{PV-DC}}} p_{\text{PV}(j,t)} \cdot C_{\text{PV}(j,t)} \cdot \pi(s) + \sum_{i=1}^{N_{\text{DG}}} p_{\text{DG}(i,t)} \cdot C_{\text{DG}(i,t)}
\]

\[
\text{HHI} = \frac{\left( \sum_{e=1}^{N_e} P_{E\text{SS}}(e,t,s) \cdot C_{E\text{SS}}(e,t) \cdot \pi(s) \right)^2 + \sum_{v=1}^{N_v} \left( P_{E\text{V}}(v,t,s) \cdot C_{E\text{V}}(v,t) \cdot \pi(s) \right)^2 + \cdots}{\sum_{j=1}^{N_{\text{PV-DC}}} \left( P_{\text{PV}(j,t)} \cdot C_{\text{PV}(j,t)} \cdot \pi(s) \right)^2 + \sum_{i=1}^{N_{\text{DG}}} \left( P_{\text{DG}(i,t)} \cdot C_{\text{DG}(i,t)} \right)^2} \times 10000 / \text{Gen}^2
\]
3.3.2. Index of the three largest bidders. This index establishes that to prevent one of the largest bidders from becoming indispensable to meet the demand. In commercial terms, if a bidder knows that its generation plant must be included regardless of the price, it can take advantage of what results in situations not optimal for the settlement of the price. Equation (7) represents the index of the three largest bidders and its calculation is demonstrated for a single period, that is, the calculation must be made for each period of the 24 and verify that the available generation is greater than 100%. Equation (7) is represented by the first term that represents the total supply of the industry, followed by the second term that represents the second and third largest bidder, and the last term that appears in the parentheses "max" represents the maximum generation. All terms are divided into total demand.

\[ \text{RSI3} = (\text{Gen}_t - \text{Gen}_l)^2 - \max \left( P_{\text{ESS}^-}(e.t,s) \cdot C_{\text{ESS}^-}(e.t) + P_{\text{EV}^-}(v.t.s) \cdot C_{\text{EV}^-}(v.t) \right) \]

\[ \cdots + P_{\text{DG}(l,t)} \cdot C_{\text{DG}(l,t)})/ \sum_{l=1}^{N_{t_{\text{l}}}} P_{\text{curt}(l,t,s)} \cdot C_{\text{curt}(l,t,s)}) \times 100 \]  

3.3.3. Variable neighborhood search - differential evolutionary particle swarm multiobjective. The multiobjective implementation of the VNS-DEEPSO-MO algorithm is based on two rules depending on the population. The VNS takes a fixed value of scenarios according to the convenience of the aggregator and the DEEPSO algorithm completes the defined population. Figure 2 and Figure 3 present the grouping criteria according to Pareto fronts. In the first populations there are usually several fronts of Pareto, there will be two types of population, the initial one and the actual one that evolved, to define the new population the size remains constant so there will be a cut front and the best individuals are selected using the hypervolume metric, then two fronts are taken for this metric the first front and the front cut.

A small value indicates a greater proximity of the population from the cutting front to the first front, therefore the values are organized from lower to higher for the cut front. This grouping criterion seeks that the cutting front approaches the first Pareto front, it is clarified that the first Pareto front is the closest to the optimum.

The niching case 2 occurs when all the values are located in the first front, therefore the criterion of Figure 3 seeks a better distribution of the population the first Pareto front uses as a grouping criterion the measure of the perimeter of the two neighbors’ values with greater perimeter are ideal. The population is organized from highest to lowest and to ensure that the two limit values are not lost, the perimeter is measured by taking the extreme values of the first Pareto front.

3.3.4. Test problems. The operation of the algorithm is verified with the test problems SCH, CONS, ZDT2 and FON. These functions serve to test the convergence properties of the new multiobjective algorithm.

4. Results and discussion
The new multiobjective algorithm presents very good results for the test problems, ZDT2, FON, SCH and CONS presenting a uniform distribution and close to the Pareto front. In addition, the non-mastered front of the VNS-DEEPSO-MO algorithm determines the most convenient value for the microgrid
according to the lowest costs. Figure 4 and Figure 5 show that the restrictions are met as desired, that is, in terms of a more realistic study in which the results can be altered by the desire of generating agents to exercise market power. In this study that effect is mitigated. Figure 4 shows the Herfindahl-Hirschman index of less than 2500, that is, this is a competitive market in which generators supply energy by merit. In Figure 5 the index of the 3 largest bidders shows that in all cases energy can be supplied without relying on the 3 largest bidders (in all cases 100% is exceeded).

Figure 6 shows that results are the expected, that is, for 24 hours, the energy supply for the demand was guaranteed, and with a higher energy consumption between 12 and 2 pm. Figure 7 shows the power generation capacity taking the 34 electric vehicles as storage systems. In terms of generation they make an important contribution in the offer from 1 to 6 hours, and from 20 to 24 hours (they can generate up to 110 kW for these periods).

### 5. Conclusions

The search for new algorithms for smart microgrid management is essential due to the complexity in their operation, the VNS-DEEPSO-MO multiobjective algorithm was validated with the test problems SCH, CONS, ZDT2 and FON, showing good performance in terms of proximity and distribution in front of Pareto. Therefore, it is evident that the proposals of: 1) Pareto front and 2) the first Pareto front respectively improve the proximity and distribution of the first front. In the case of the study, the advantage of having prosumers in a power grid is evident, the Herfindahl-Hirschman index measures are below 2500 and the generation is greater than 100% without requiring the 3 largest bidders for all periods, in fact, it results in a competitive market and non-dependence on the market prices of the largest bidders. The methodology is effective because the supply of continuous energy for demand was guaranteed, and also the continuous generation of energy allows to increase the profits of the entire micro network, this is due to the sale of energy. In future research, the performance of the VNS-DEEPSO-MO algorithm with more test problems should be evaluated. In addition, the performance of a traditional network compared to a smart grid should also be compared.
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