Optimization of Grid-Connected Microgrids with Residential Prosumers Using an Improved Genetic Algorithm

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Abstract

With the continuous increase of the microgrids' implementation into the power system the problem of maintaining their stability and balance arises and the necessity to adopt an appropriate energy management system emerges. This paper analyses the optimization of the grid-connected microgrid, which consists of a photovoltaic generator, a wind generator, a battery, and residential prosumers. The paper presents the application of an improved genetic algorithm, which takes into consideration the voltage levels on the connection points of the generators and the prosumers, as well as the trading with the local grid. The proposed algorithm suggests the usage of the standard genetic algorithm with the improvement in the fitness and selection process. The results of the simulation are compared with the results obtained when using a standard genetic algorithm with five different types of selection.

Keywords

Genetic algorithm, optimization, microgrids, renewable energy sources

1. Introduction

Grid-connected microgrids have an important role in the incorporation of renewable energy sources (RES) in the power grid, enabling their power to be used by local consumers. This decreases the power losses and the costs of power transmission and distribution. However, the dynamic trade between the prosumers in the microgrid, and between the microgrid and the power system, in addition to the increased number of generators and prosumers, makes the optimization problem and the maintaining of the stability in both systems, more complex. Therefore, it is necessary to use an optimization technique considers both the technical constraints of the equipment and limitations of the local power grid. Additionally, it should ensure that the microgrid maintains stable frequency and voltage levels, and avoids any distruptions to the operation of the local power grid.

This paper uses an improved Genetic Algorithm (GA) for optimal unit commitment in grid-connected microgrids with residential prosumers. In the literature, many different approaches to solving this problem and many other optimization techniques can be found [1]. Although the

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usage of GA for solving this type of problem is not a novelty, it provides security and simple application with flexible mathematical interpretation of the problem.

The proposed algorithm is based on the standard GA with improved fitness and selection process. The selection considers the fitness score of the randomly generated population and chooses the individuals with higher fitness scores to reproduce the next generation. In this manner, the next generation has the potential to inherit enhanced genes and provide a better solution to the problem. This accelerates the optimization process, providing an improved solution. The proposed algorithm is tested on a microgrid consisting of five prosumers equipped with photovoltaics and additional battery, photovoltaic, and wind generators connected to the microgrid. The complexity of the problem comes from the power exchange between the prosumers, and the whole community, and the local power grid.

The results are compared to the ones obtained when other selection methods are used, including Roulette Wheel, Remairner Selection, Tournament Selection, Stochastic Universal Sampling (SUS), and Uniform Selection. Based on the comparison, it can be concluded that the proposed algorithm does lead to an improvement.

2. Problem Definition and Literature Review

The term microgrid defines a system consisting of microgenerators of electrical energy (photovoltaics, wind generators, fuel cells, diesel generators, etc.) and consumers that operate as a single unit and provide electrical energy to a certain area or a group of consumers near them [2]. The increased implementation of the RES and the creation of microgrids, not only for satisfying the consumption to distant and unreachable places, and in the rural areas, but also in the suburbs is due to the need for the generation of electrical energy from ecologically acceptable sources and lowering the costs for transmission and distribution. The need for optimization of the microgrids arises from the interconnection and energy exchange of the installed generators and the prosumers in between, as well as the energy exchange with the local grid. The contemporary microgrids are equipped with a larger number of generators (photovoltaics, wind generators, small hydropower plants, diesel or hydrogen generators, batteries, etc.), whose power generation is stochastic due to its dependency on the weather conditions. This increases the complexity of the optimization problem. Additional influence is the connection of the microgrid to the local distribution grid, whose conditions for stable operation have to be respected since the microgrid operation cannot interfere with the stability and balance of the local grid.

The microgrids' optimization is mostly based on production and distribution costs' minimization or the maximization of the profit from trading with the local grid. Additionally, the optimization covers the parameters that define the stability and resilience of the microgrid. In [2] an Artificial Bee Colony algorithm is used for costs and power loss optimization of a microgrid with six prosumers, each of them with a different type of consumption (residential, commercial, industrial), different type of power generator, and a battery. Reference [3] presents the implementation of the Hierarchical Genetic Algorithm for maximization of the profit from trading with the local grid, defining the price of the electrical energy according to the usage time. In [4] an Accelerated Genetic Algorithm for solving optimization problems in microgrids with multiple variables, is proposed. The optimization function unites the maintenance and exploitation costs of the microgrid, the diesel generator fuel costs, and the gas emission costs when the diesel generator is used, as well as the costs for element replacement. In [5] a genetic algorithm for optimal unit commitment in microgrids consisting of wind generators, photovoltaics, batteries, and diesel generators, is used. In [6] an improved genetic algorithm for optimal unit commitment in microgrids, with better convergence is used. In [7], penalty costs are considered for a model based on a genetic algorithm. The analysis of voltage and frequency, using a genetic algorithm is presented in [8]. Reference [9] presents a simulated optimization of dispersed generation and system for storing excess power in grid-connected and islanded microgrids. The paper analyses two alternative optimization functions. The first one minimizes the annual power losses, and the second one minimizes the costs of power production. The best results are maintained when the microgrid trades with the local grid and it has a storage system installed. Reference [10] suggests an Adaptive Genetic Algorithm for the optimization of microgrids which consists of photovoltaic generators, wind generators, battery and diesel generators, and electrical vehicles that are charged from the network. The acceleration of the genetic algorithm is done by filtrating the population to achieve the optimal solution faster. The proposed algorithm is compared to the results obtained by using the FireFly Algorithm and Particle Swarm Optimization. In [11] a Non-Dominated Sorting Genetic Algorithm (NSGA-II) is used for a microgrid with pumped storage hydropower and a battery as systems for storing the excess power. The optimization function considers the investment costs and minimizes the carbon dioxide emission. In [12] a Multi-Objective Genetic Algorithm is used for a grid-connected microgrid consisting of a photovoltaic generator, wind generator, and battery. A forecasting method for predicting power production and consumption is used, and a comparison between fixed and variable grid prices is made. In [13] a hybrid algorithm of Particle Swarm Optimization and Genetic Algorithm is suggested. The algorithm is used for voltage and frequency control in an islanded microgrid. The goal is the greater usage of electrical energy produced locally by the dispersed generators. In [14] an optimization is done using a genetic algorithm for minimizing the voltage drop through sudden changes in load in an islanded microgrid.

In this paper, the accent is on the optimal unit commitment in the microgrid, to satisfy the consumption and stable voltage in the nodes, as a condition for a sable and balanced operation. For that purpose, a genetic algorithm is used.

3. Problem Solution

This paper proposes an improved genetic algorithm used for the optimization of the unit commitment of grid-connected microgrids with connected residential prosumers. The method takes into consideration the stochastic nature of the weather conditions and the power consumption. The optimization functions take into consideration the costs for buying power from the local grid when there is a shortage of power in the microgrid, as well as the profit for selling power to the grid when there is an excess, under defined technical constraints and the voltage levels in the connection points. For the analysis, three different scenarios were considered.

3.1. Scenario I

In the first scenario, the power generation from the photovoltaic generator and wind generator exceeds the power consumption. The relation is given in (1). The consumption is satisfied with the power generation from the residential prosumers or with the power exchange among other members of the community.

$$P_{\text{pv\_load,m}} \geq P_{\text{load,m}}, m = \overline{1{,}5} \tag{1}$$

where, $P_{\text{pv\_load,m}}$ denotes the power generated from the photovoltaic generators on the residential objects, $P_{\text{load,m}}$ represents the power consumption from each of the residential objects, and m denotes the number of the residential object.

In that case, the excess power in the system, given in (2), is stored in the battery or sold to the grid. If the battery has reached the minimum State of Charge (SOC), then it has to be charged enough so it can provide power to the consumers in the next 10 hours, and the excess power has to be sold to the grid. If the battery is partially full, then a decision is made if the excess power should be stored in the battery or sold to the grid. In case the battery is full, then the total excess power is sold to the grid.

$$P_{\text{excess}} = \sum_{m=1}^{5} \left(P_{\text{load,m}} - P_{\text{pv\_load,m}}\right) + P_{\text{pv}} + P_{\text{wind}} \tag{2}$$

where P_{excess} denotes the excess power generated from the photovoltaic generators on the residential objects that are not consumed, P_{pv} represents the power generated from the photovoltaic generator connected to the microgrid, and P_{wind} represents the power generated from the wind generator.

3.2. Scenario II

In the second scenario reviewed, the power consumption of the residential prosumers exceeds the power generation from the photovoltaic generations installed on them, and the consumption is satisfied by the photovoltaic and wind generator connected in the microgrid, presented with (3) and (4).

$$P_{\text{load,m}} > P_{\text{pv\_load,m}}, m = \overline{1{,}5} \tag{3}$$

$$P_{\text{needed}} = \sum_{m=1}^{5} \left(P_{\text{load,m}} - P_{\text{pv\_load,m}}\right) \tag{4}$$

where P_{needed} represents the needed power to satisfy the consumption.

If there is excess power, then it is stored in the battery or sold to the grid, as presented in (5).

$$P_{\text{excess}} = P_{\text{pv}} + P_{\text{wind}} - P_{\text{needed}} \tag{5}$$

3.3 Scenario III

The third scenario analyses the situation when there is not enough power generation to satisfy the consumption, so the needed power is taken from the battery or it is bought from the grid. The relations are given with (6) and (7)

$$P_{\text{wind}} + P_{\text{pv}} \leq P_{\text{needed}} \tag{6}$$

$$P_{\text{needed\_sys}} = P_{\text{needed}} - P_{\text{pv}} - P_{\text{wind}} \tag{7}$$

where $P_{\text{needed\_sys}}$ represents the needed power to satisfy consumption after extracting the power generated from photovoltaic and wind generators.

The proposed algorithm unites two optimization functions. The first one minimizes the operational costs of the microgrid, and the second one limits the voltage drop to the generators to ±5%, and to the consumers to ±10%. The functions are presented with (8) and (9).

$$F_1(P_i) = \max\left\{\sum_{i=1}^{T}\left(B_{\text{DER,i}} - C_{\text{grid,i}}\right)\Delta t\right\} \tag{8}$$

$$F_2(P_i) = \min\left\{\left(\frac{P_{\text{pv}} + P_{\text{wind}} + \sum_{n=1}^{5}\left(P_{\text{pv}_{\text{load}},\text{n}}\right) + P_{\text{bat\_dis}} - P_{\text{bat}_{\text{ch}}} + P_{\text{buy}} - P_{\text{sell}}}{V_{\text{r}}} \cdot r + \frac{Q_{\text{grid}} - Q_{\text{wind}} + Q_{\text{buy}}}{V_{\text{r}}} \cdot x\right) \cdot l - \Delta V\right\} \tag{9}$$

where, $B_{\text{DER,i}}$ represents the total profit and $C_{\text{grid,i}}$ represents the total costs from microgrid operation. T represents the analyzed period, and Δt represents the time interval for data sampling (1 hour). $P_{\text{bat\_dis}}$ denotes the power discharged from the battery and $P_{\text{bat_ch}}$denotes the power charged. P_{buy} denotes the power bought from the grid, and P_{sell} denotes the power sold to the grid. Q_{grid}, Q_{wind}, and Q_{buy} represent the reactive power taken from the grid to the load, the reactive power that the wind generator generates, and the reactive power bought from the grid to maintain stable voltage levels, respectively. The variable V_{r} is the rated voltage, and r and x are the resistance and the reactance in Ohms/meter, respectively. The distance between the nodes is denoted with l, and the permitted voltage drop is denoted with ΔV.

The total profit of the microgrid is presented with (10). It is calculated as a sum of the profit from generating power from the installed generators and selling the excess power to the grid:

$$B_{\text{DER}} = P_{\text{pv}} \cdot p_{\text{pv}} + P_{\text{wind}} \cdot p_{\text{wind}} + P_{\text{sell}} \cdot p_{\text{sell}} + P_{\text{bat\_dis}} \cdot p_{\text{bat}} \tag{10}$$

where, $p_{\text{pv}}, p_{\text{wind}}, p_{\text{sell}}$, and p_{bat} denote the prices for power generation from the photovoltaic generator, the wind generator, the price for selling the excess power to the grid, and the price for discharging the battery, respectively.

The costs for storing the excess power in the battery and the costs for buying power from the grid are calculated as the product of thecc power and the appropriate prices, as shown in (11):

$$C_{\text{grid}} = P_{\text{buy}} \cdot p_{\text{buy}} + P_{\text{bat}_{\text{ch}}} \cdot p_{\text{bat}} \tag{11}$$

where, p_{buy} denotes the price for buying power from the grid, photovoltaic generator.

The optimization method is based on the genetic algorithm. The proposed algorithm makes a decision, at each of the analyzed hours, what solution is more financially cost-effective, prioritizing the power generated from the RES. If there is excess power, the algorithm decides whether to store it in the battery or sell it to the grid. Also, if there is a shortage of power, it decides whether it should take it from the battery or buy it from the local grid. Since the microgrid is connected to the local grid, the voltage levels have to be regulated through every power trading with the grid, preventing high oscillations. The maximal generated power from the RES is presented with (12), (13), and (14), for the photovoltaic generator, wind generator, and the photovoltaic generators installed on the residential objects, respectively.

$$P_{\mathrm{pv,min}} \leq P_{\mathrm{pv,i}} \leq P_{\mathrm{pv,max}}, \forall i \in [0, T] \tag{12}$$

$$P_{\mathrm{wind,min}} \leq P_{\mathrm{wind,i}} \leq P_{\mathrm{wind,max}}, \forall i \in [0, T] \tag{13}$$

$$P_{\mathrm{pv\_load,min}} \leq P_{\mathrm{pv\_load,i}} \leq P_{\mathrm{pv\_load,max}}, \forall i \in [0, T] \tag{14}$$

The maximal and the minimal power charged and discharged from the battery, as well as the SOC, are given in (15) and (16).

$$0 \leq P_{\mathrm{bat,i}} \leq P_{\mathrm{bat,max}}, \forall i \in [0, T] \tag{15}$$

$$0 \leq SoC_{\mathrm{bat,i}} \leq 1, \forall i \in [0, T] \tag{16}$$

To maintain a balance in the system, it is necessary to define the maximum and minimum power that the grid can take in and give, as represented in (17). In that way, the voltage variations that can occur due to sudden increase or decrease of power in the system, are reduced. These limits are regulated by the local grid to which the microgrid is connected.

$$P_{\mathrm{grid,min}} \leq P_{\mathrm{grid,i}} \leq P_{\mathrm{grid,max}}, \forall i \in [0, T] \tag{17}$$

Equations (18) and (19) show the power balance in the system. The voltage variation limits are shown in (20). Since the microgrid is connected to a low-voltage distribution grid, the voltage variations are limited to $\pm 10\%$.

$$P_{\mathrm{pv}} + P_{\mathrm{wind}} + \sum_{m=1}^{5} P_{\mathrm{pv\_load,m}} + P_{\mathrm{bat\_dis}} + P_{\mathrm{buy}} = P_{\mathrm{load}} + P_{\mathrm{sell}} + P_{\mathrm{bat\_ch}} \tag{18}$$

$$Q_{\mathrm{bat\_dis,i}} + Q_{\mathrm{buy,i}} = Q_{\mathrm{load,i}}, \forall i \in [0, T] \tag{19}$$

$$0.9 \cdot V_{\mathrm{r}} \leq V(t, i) \leq 1.1 \cdot V_{\mathrm{r}}, \forall i \in [0, n_{\mathrm{nodes}}] \tag{20}$$

Equation (21) shows the calculation of the voltage in each of the nodes. Thereby, the reference node is the node to which the last prosumer is connected:

$$V(t, i+1) = V(t, i) + \frac{(\sum P_i(t))rl + (\sum Q_i(t))xl}{V_{\mathrm{r}}}, \forall i \in [0, n_{\mathrm{nodes}}] \tag{21}$$

The proposed algorithm is shown in Figure 1. In the initialization of the parameters, the size of the population is defined and each individual is assigned a random value. The number of variables is five, and that includes the photovoltaic generator and the wind generator in the microgrid, the power exchanged with the grid (bought and sold), and the power charged or discharged from the battery. The power generated from the photovoltaic generator installed on the residential objects has a priority, meaning that it has to be used before considering taking power from the RES generator connected to the microgrid. Therefore, that power is not part of the optimization.

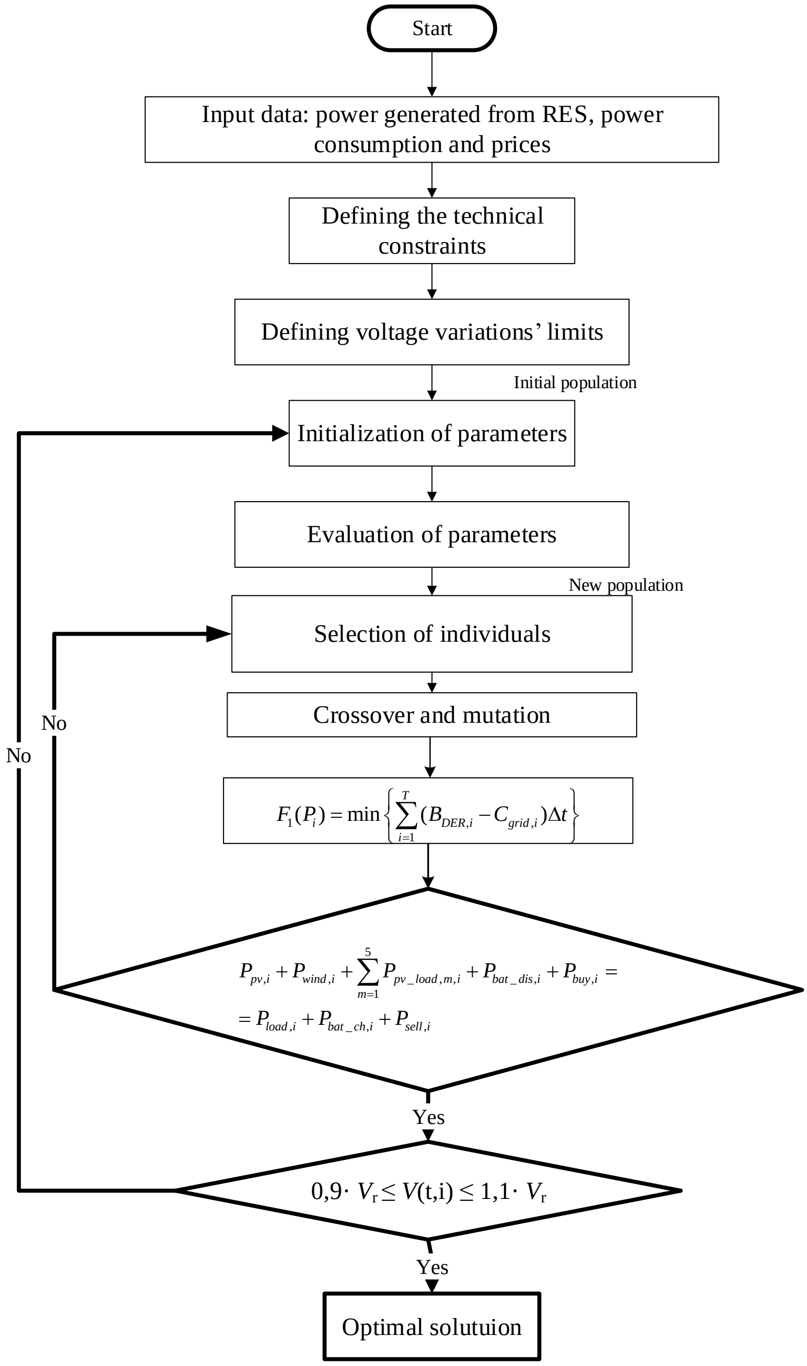

Figure 1: Flow chart of the proposed algorithm for optimization of grid-connected microgrid with residential prosumers.

The optimization starts with a variable's initialization. All of the variables are set with randomly generated values, 100 in total. Those are the starting values that have to be checked through the fitness process and given a fitness score. Those values are called individuals. The algorithm is programmed in Matlab. The custom function for evaluation of the quality of the potential solutions is defined with (22).

$$expectation_i = \frac{scores_j \cdot nParents}{\sum_{j=1}^{n} scores_j}, \forall j \in [0, n] \quad (22)$$

where, *scores* denotes a vector of scalars, one for each member of the population, *nParents* is the number of parents needed from this population, n is the vector length of scores, p is the vector length of *nParants*, and *expectation* is a column vector of scalars of the same length as *scores*, giving the scaled values of each member of the population.

The next phase is the selection process. This paper proposes a modification in the selection process so that the individuals with the higher fitness score to be chosen to produce the next generation. In this paper, the selection condition is presented with (23).

$$expectation_i \geq \max(expectation_i) \cdot \alpha, \forall i \in [0, n] \quad (23)$$

The weight factor α has a defined value between 0 to 1, and it determines the condition for selection. In this paper, after several tests, it was determined that the weight factor has an optimal value of $\alpha = 0.95$. The probability of occurrence of the individual with the current fitness score is defined with (24).

$$p_i = \frac{expectation_i}{\sum_{i=1}^{n} expectation_i}, \forall i \in [0, n] \quad (24)$$

Equation (25) shows the process of choosing individuals that will produce the next generation. For that purpose, a build-in function in Matlab, for generating random numbers under defined conditions, is used.

$$parents = \text{randsample}(accepted, nParents, true, p) \quad (25)$$

where *accepted* is a set of accepted individuals that meet the requirement in (23), *nParents* defines the size of the set that needs to be generated, *true* indicates that the randomly generated value can appear multiple times in the sequence, and p is the probability that the accepted individual has an appropriate value.

In the next step through crossover and mutation, a new generation of individuals is generated. Then the new set of individuals goes through the fitness process. If no conditionally optimal solution can be found, new randomly generated values are set to the variables.

4. Simulation & Results

The proposed algorithm is tested on a case of five residential prosumers equipped with photovoltaic generators, coupled in a grid-connected microgrid with photovoltaic and wind generators. The microgrid is also equipped with a battery, as shown in Figure 2.

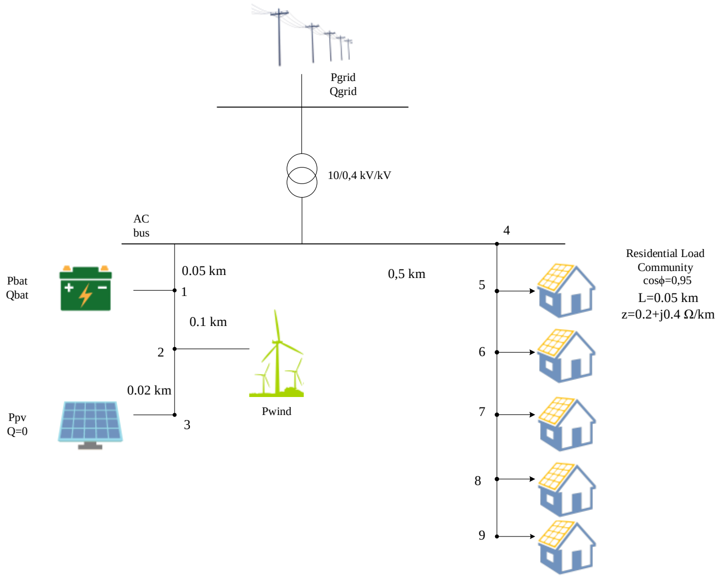

Figure 2: Topology of the analyzed microgrid.

The photovoltaic generators installed on the residential objects are designed to satisfy the consumption in days with maximum power production. If there is not enough power, it is provided by the photovoltaic or wind generator connected to the microgrid, from the battery, or the grid. Since the optimization takes into consideration the voltage in the nodes, to maintain stable voltage levels, reactive power is also taken from the grid. The analysis is done over 168 hours.

Table 1 shows the technical constraints of the installed distributed generators in the microgrid and on the residential objects, the battery, and the power trade with the grid.

Table 1
Technical constraints of the installed equipment.

Parameter	Meaning	Value	Unit
P_{pv}	Installed capacity of the photovoltaic generator	10	kW
P_{wind}	Installed capacity of the wind generator	10	kW
P_{pv_load}	Installed capacity of the photovoltaic generators installed on the residential objects	6	kW
P_{bat_ch}	Maximal charge power	25	kW
P_{bat_dis}	Maximal discharge power		
P_{buy_max}	Maximum power bought from the grid	45	kW
P_{sell_max}	Maximum power sold to the grid	30	kW
$P_{capacity}$	Battery capacity	200	kWh
SoC_{bat_min}	Minimal battery state of charge	10	%
SoC_{bat_max}	Maximal battery state of charge	100	%
η_{ch}	Efficiency coefficient of charge/discharge	95	%
η_{dis}			

In Table 2 the prices for power production from the generators and power trading with the grid are shown, and in Table 3 the obtained results are shown.

Table 2
Electricity prices

Unit	Nomenclature	Price (€ct)
Photovoltaic generator	p_{PV}	55
Wind generator	p_{wind}	46
Power sold to the grid	p_{grid}	10
Power bought from the grid		
○ I tariff price	p_c	2.8
○ II tariff price	p_p	6.9
Battery charge/discharge	p_{bat}	3
Excess reactive power consumed	p_Q	7.5

The results obtained from the proposed algorithm are compared to the results when using a standard genetic algorithm with a Roulette Wheel, Remairner Selection, Tournament Selection, Stochastic Universal Sampling (SUS), and Uniform Selection for the selection process. The results show that using any of the named selection methods results in a smaller profit, compared to the profit obtained when using the proposed improvement of the genetic algorithm. It shows that the interaction with the local distribution network is maximized and the power generated with the microgrid is completely used by the local prosumers. This justifies the proposed improvement.

Table 3
Comparison of the obtained results using different selection methods

Method	Roulette Wheel	Remainder selection	Tournament selection	SUS	Uniform selection	Improved GA
Total profit(€)	135,29	135,29	135,32	135,32	135,3317	**135,3328**
P_{buy} (kW)	642,527	642,527	642,885	642,885	642,885	**642,885**
P_{sell} (kW)	703,138	703,174	703,195	703,202	703,2724	**703,2795**

Figure 3 shows the optimal unit commitment in the microgrid, and Figure 4 shows the voltage variations in the analyzed nodes for 168 hours.

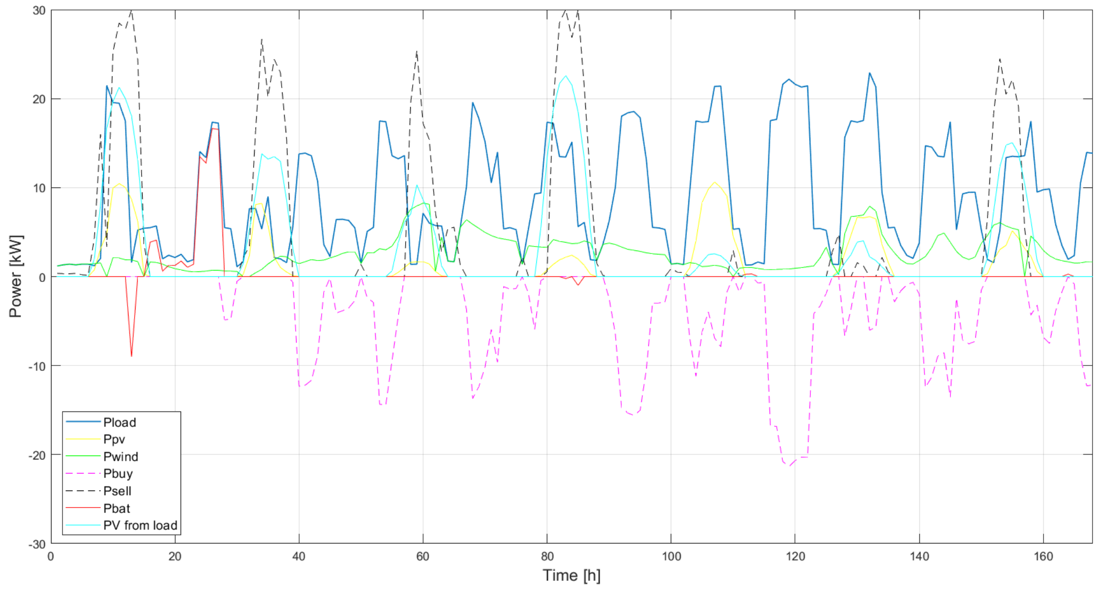

Figure 3: Optimal unit commitment

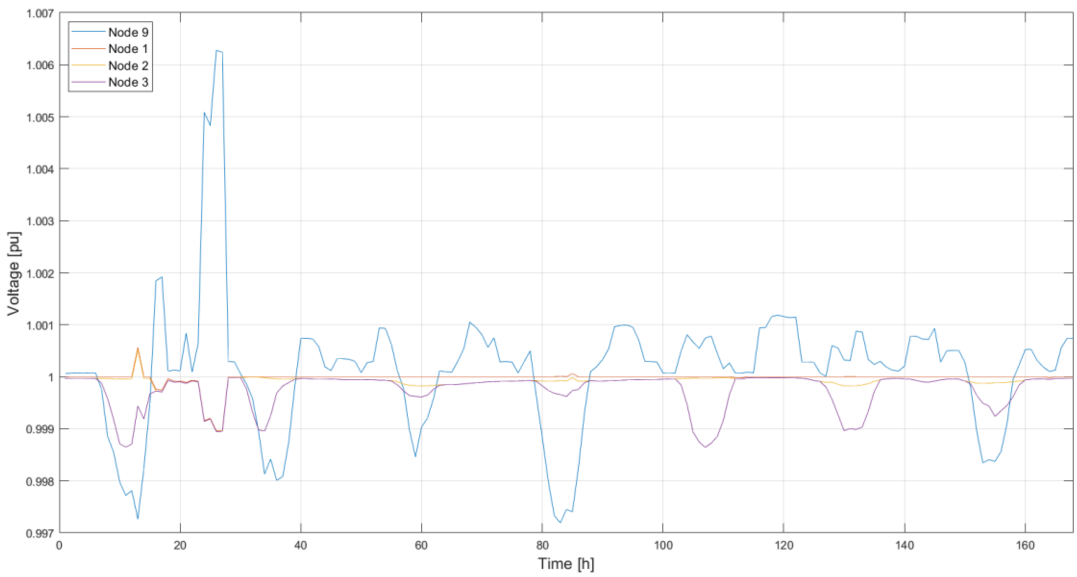

Figure 4: Voltage variations in the analyzed nodes

5. Conclusion

In this paper, an improvement of the genetic algorithm was proposed, and its application for solving the grid-connected microgrid optimization problem was analyzed. The analyzed microgrid consisted of five residential prosumers, photovoltaic and wind generators, a battery, and trade with the local grid.

The proposed algorithm defines the selection of the individuals for producing the next generation of individuals. The optimization functions maximize the profit from trading of microgrid with the local grid to which it is connected, prioritizing the usage of the power generated within the microgrid, and decreasing the power bought from the local grid while considering the voltage levels.

The results show that the proposed algorithm accelerates the optimization, providing better final results than those obtained when using a standard genetic algorithm with other selection methods. The graphical representation of the results shows that the power in the microgrid is efficiently distributed to satisfy the consumption while achieving the goal of reducing the power bought from the grid. In this way, the costs and the dependability of the microgrid on the local grid are decreased. Considering the voltage levels in the optimization process, a lower variation of the voltage is achieved.

The outcomes justify the enhancement provided by the proposed algorithm and pave the way for further research on optimizing grid-connected microgrids with different topologies.

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