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Electronics Engineering, Telecommunications, and Information Technologies

PhD THESIS

- ABSTRACT -

Smart Microgrids. Management Applications Development

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1. Introduction and thesis motivation

A microgrid is a set of components that includes power generation sources, energy storage systems and consumers. Designed for flexibility and environmental protection, microgrids often include renewable energy sources such as wind turbines, geothermal generators, biomass / biogas generators and photovoltaic panels to meet electricity demand. As the world's governments begin to impose legislation to cover an increasing percentage of energy needs using "green" sources, optimizing the operating costs of microgrids is becoming a necessity.

This thesis, entitled "Smart Microgrids. Development of Management Applications", aims to optimize the operating cost of an isolated microgrid and experimentally validate the solutions.

2. Thesis purpose and objectives

The main purpose of the thesis is to minimize the operating cost of an islanded microgrid by using Day-Ahead Scheduling methods (algorithms). Minimizing the operating cost is, in itself, an optimization problem with a single objective: to obtain a daily operating cost as low as possible while fully covering the energy needs and the using the microgrid elements within nominal parameters. The limitation of Day-Ahead Scheduling methods consists in predicting the weather conditions and the energy requirements during the day. These optimization methods will actually obtain the calculated results only if the two predictions are perfect. Thus, the secondary purpose of the thesis is to develop and validate a real-time control method for the microgrid that uses the operating program obtained after optimizing the cost and to adapt it in situations where at least one of the predictions does not correspond to reality.

As a result, the thesis objectives are the following:

- Optimizing the operating cost of the proposed microgrid;
- Validating the implemented optimization methods;
- Developing, implementing and validating a real-time control method of the microgrid.

3. Research methodology

The methodology used involves the description of the proposed microgrid and the definition of the operating costs of its elements, which will then be used to mathematically define the optimization problem. The optimization objective is to determine a operating program of the microgrid so as to obtain a cost as low as possible, but without contradicting the main purpose of the microgrid, namely to cover the entire energy needs of consumers. The optimization problem is solved using 3 methods, two of which are general and used in the literature for a wide range of optimization problems, and one is a method developed for the proposed microgrid. The results of the 3 methods are compared and validated using a simulation. The personalized method is experimentally validated and used as a basis for the implementation of a real-time control method for the microgrid.

Following the analysis of the results, they were disseminated through 6 papers published at international conferences, 5 of which are WOS indexed and one is BDI (IEEE) indexed.

4. Thesis structure

The structure of the paper includes two parts: *The state of the art* (chapters 1 and 2) and *The personal contribution* (chapters 3-8).

Chapter 1 is introductory and describes the historical and current energy production using renewable sources. Various architectures and control methods of microgrids are described, and energy management is defined as an optimization problem.

Chapter 2 represents the theoretical fundamentals and defines notions of probability theory, random variables, probability distributions, mathematical optimization and energy management. Optimization methods are classified following a bibliographic study.

Chapter 3 refers to the mathematical formulation of the optimization problem. The proposed microgrid, illustrated in Figure. 1, consists of 3 power generation units: a set of 12 250 W ET-Solar photovoltaic panels connected to the microgrid using the 3.8 kW SMA Sunny Boy 3600TL-21 inverter (1), a geothermal generator (2) and a biogas generator (3), both 1.5 kW. The energy needs of consumers (4) are covered using the 3 generating units and the energy storage system (5), consisting of 8 12 V, 250 Ah VRLA batteries, connected to the microgrid using the SMA Sunny Island 6.0H inverter, with a storage capacity of 24 kWh. The use of each energy source is programmed and controlled by the energy management system (6) according to the meteorological and geographical characteristics of the location where the microgrid is located: Bihor County, Romania. The main load is a vegetable greenhouse. This microgrid is designed to operate in islanded mode.

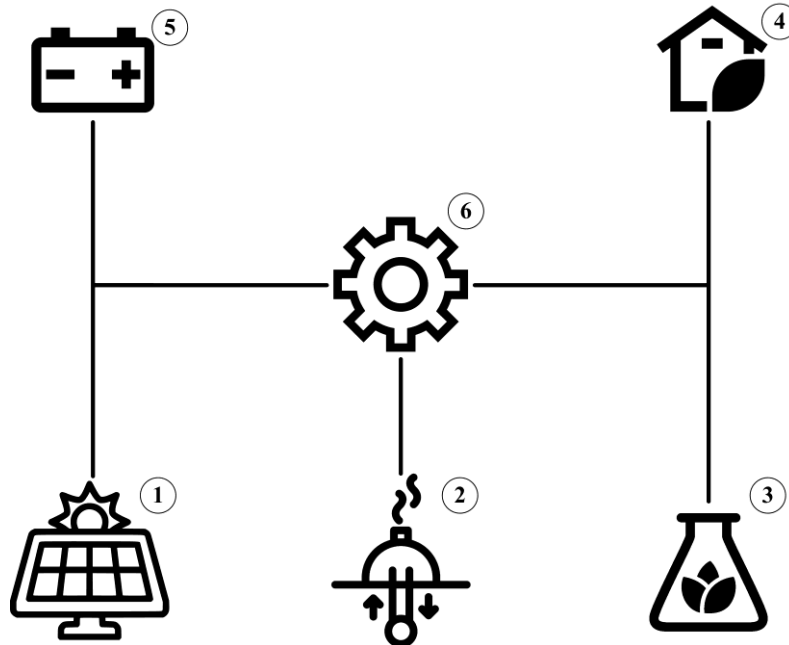


Figure 1. The proposed microgrid

In order to optimize the operating cost of the microgrid, the variable OPEX values of its elements are relevant, and they can be observed in Table 1.

Table 1. Variable OPEX values for the elements of the proposed microgrid

		Photovoltaic panels	Biogas generator	Geothermal generator	Batteries
Variable OPEX [\$/kWh]	from	0,000	0,020	0,080	0,336
	up to	0,000	0,030	0,200	0,672

The optimization objective is defined by equation 1:

$$\min f(X) = \sum_{t=1}^{24} \left(\begin{aligned} &E_{PV}(t) \cdot C_{PV} + E_{Geo}(t) \cdot C_{Geo} \\ &+ E_{Bio}(t) \cdot C_{Bio} + E_{BatDsch}(t) \cdot C_{Bat} \\ &- E_{BatCh}(t) \cdot C_{Bat} + E_{Excess}(t) \cdot C_{Excess} \\ &+ E_{Undel}(t) \cdot C_{Undel} \end{aligned} \right) \quad (1)$$

where:

- $f(X)$ is the objective function of the optimization problem;
- X is the solution matrix for the optimization problem;
- $E_{PV}(t)$ = energy [Wh] generated by the photovoltaic panels in the $[t-1,t)$ interval;
- $E_{Geo}(t)$ = energy [Wh] generated by the geothermal generator in the $[t-1,t)$ interval;
- $E_{Bio}(t)$ = energy [Wh] generated by the biogas generator in the $[t-1,t)$ interval;
- $E_{BatDsch}(t)$ = energy [Wh] discharged from the batteries in the $[t-1,t)$ interval;
- $E_{BatCh}(t)$ = energy [Wh] charged into the batteries in the $[t-1,t)$ interval;
- $E_{Excess}(t)$ = excess energy [Wh] produced in the $[t-1,t)$ interval;
- $E_{Undel}(t)$ = uncovered load demand [Wh] in the $[t-1,t)$ interval;
- C_{PV} , C_{Geo} și C_{Bio} represent the operating costs of the generation elements;
- C_{Bat} represents the operating cost of the batteries;
- C_{Excess} și C_{Undel} represent monetary penalties for generating excess energy and not covering the load demand respectively.

Minimizing the objective function f consists of searching for the optimum values of the decision variables: $E_{PV}(t)$, $E_{Geo}(t)$, $E_{Bio}(t)$, $E_{BatDsch}(t)$, $E_{BatCh}(t)$, $E_{Excess}(t)$ și $E_{Undel}(t)$. The optimization problem has an equality constraint (ec. (2)) and two inequality constraints (ec. (3) and (4)):

- Energy balance:

$$h(X) = 0 \quad (2)$$

$$h(X) = E_{Gen}(t) + E_{Bat}(t) + E_{Excess}(t) + E_{Undel}(t) + E_{Load}(t), t = 1, \dots, 24$$

where:

- $E_{Gen}(t) = E_{PV}(t) + E_{Geo}(t) + E_{Bio}(t)$ (energy generated in an hourly interval);
- $E_{Bat}(t) = E_{BatDsch}(t) - E_{BatCh}(t)$ (energy charged in/dischd from the batteries in an hourly interval);
- $E_{Load}(t)$ = load demand in an hourly interval.
- Energy storage system limits:

$$g_1(X) \geq 0 \quad (3)$$

$$g_1(X) = E_s(t), t = 1, \dots, 24$$

$$\begin{aligned} g_2(X) &\geq 0 \\ g_2(X) &= E_{SLimit} - E_s(t), t = 1, \dots, 24 \end{aligned} \tag{4}$$

where:

- $E_s(t) = E_s(t-1) - E_{Bat}(t)$ (energy stored in the batteries at the end of an hourly interval);
- $E_{SLimit}(t) = 24 \text{ kWh}$ (the nominal storage capacity).

The $E_s(t)$ values included in the solution generated by the optimization method are used for calculating the State of Charge (SoC) values for each time interval as follows:

$$SoC(t) = \frac{E_s(t) \cdot 100}{E_{SLimit}} \tag{5}$$

For a solution to be considered valid the values of the $E_{Excess}(t)$ and $E_{Undel}(t), t = 1, \dots, 24$ decision variables must be 0, their purpose being entirely theoretical. In reality, a situation in which $E_{Undel}(t) \neq 0$ can only appear if $E_s(t) = 0$. Otherwise, the load demand will be covered by discharging the batteries. Similarly, we can only have an $E_{Excess}(t) \neq 0$ if $E_s(t) = E_{SLimit}$. This case leads to the thermal dissipation of the excess energy. Otherwise, the unused energy will be used to charge the batteries. The two decision variables were used in the optimization problem for easier verification of the solutions.

The load profile used in the calculations is estimated for each time interval. Since the algorithms are used for the advance planning of resource use, the results obtained are evaluated according to the daily operating cost of the microgrid.

Chapter 4 describes the implementation and testing of the Harmony Search (HS) method. This is a metaheuristic optimization method inspired by the process by which musicians obtain a pleasant melody. In this case, the aesthetic quality of the music is replaced by the objective function. Because the tones of the instruments influence the overall quality of the music, they are represented by the decision variables of the optimization problem, and form the solution matrix.

In the optimization process, a decision variable can receive a value from the harmony memory (HM), receive a value from the HM that has been slightly adjusted, or receive a random value from the possible range defined at the beginning of the optimization algorithm. The number of harmonies in the HM is called the harmonic memory size (HMS). There are three parameters that influence the performance of the algorithm: harmony memory considering rate (HMCR), pitch adjustment rate (PAR) and bandwidth (bw). The probability of choosing a harmony from HM is HMCR. PAR represents the probability of adjusting a harmony in HM. bw is used to achieve a balance between the local optimization process and the global one. If a value from the HM is modified the adjustment is made as follows:

$$newValue = oldValue \pm r \cdot bw \tag{6}$$

where r is a randomly generated number in the $[0,1)$ interval.

After the decision variables receive new values and a new possible solution is formed, it is evaluated using the objective function. If the new solution meets all the constraints and is better than the most unfavorable solution in HM, then the latter will be replaced.

The operating costs obtained for a typical day of each month of the year using the HS method are compared with those obtained using the Mixed Integer Linear Programming (MILP) method. The latter is a classic, mathematical method, used to solve this type of optimization problem, its results being used as a reference during the implementation and testing of the optimization methods presented in this thesis. For each input data set, the HS method generated solutions with lower costs than the MILP method.

Chapter 5 describes the implementation and testing of Particle Swarm Optimization (PSO). This is a population-based stochastic optimization method used to solve both continuous and discrete optimization problems. It is part of the swarm intelligence discipline. In this method simple software agents, called particles, move through the defined search space. The position of a particle is a possible solution to the problem. Each particle is looking for more and more favorable positions by changing its speed according to rules inspired by the behavior of schools of fish and flocks of birds in search of food.

In PSO the swarm consists of a set of particles. The position of a particle corresponds to a possible solution to the given optimization problem, represented by an objective function. At any given time, the particle has an associated position and velocity. The implementation begins with the generation of random positions of particles within the search space. During running, the velocities and positions of the particles are changed iteratively until the stopping condition is reached. The velocity and position of a particle are updated according to ec. (7) și (8):

$$V_{it+1} = wV_{it} + \varphi_1 r_1 (b_{it} - X_{it}) + \varphi_2 r_2 (l_{it} - X_{it}) \quad (7)$$

$$X_{it+1} = X_{it} + V_{it+1} \quad (8)$$

where w is the inertia weight, φ_1 and φ_2 are cceleration coefficients, r_1 and r_2 are randomly generated values in the $[0,1]$ interval, b_{it} is the best position in the particle's history, and l_{it} is the best position in the swarm's history.

The results obtained using the PSO method are compared with those obtained using the MILP and HS methods. The MILP method has been surpassed by the two stochastic methods in almost every month. The exceptions are the operating costs obtained by the PSO method for days in June, July and August. The PSO method generates good results in the cold months of the year, while the HS method generates good results in the warm months.

Chapter 6 describes the development, implementation and testing of the personalized optimization method, called the stochastic-dynamic (SD) method. Unlike the HS and PSO methods, the SD method is an optimization method created specifically for the optimization problem defined above. The purpose of developing a customized optimization method was to avoid the shortcomings observed during the implementation and testing of general optimization methods. The two optimization methods described above use initial populations of randomly generated solutions and complicated rules for generating new solutions, which involve a large number of parameters whose values must be discovered empirically depending on the optimization problem for which they are applied. Both features caused problems during testing and troubleshooting the implemented programs and determined the need to apply fixes on the offered solutions. For these reasons the decision to implement a new optimization method, that has a stochastic character and is easy to configure, was made.

The SD optimization method aims to avoid the above-mentioned difficulties by eliminating the initial population and using a simpler method of generating possible new solutions. This is achieved by using two parameters, α and β . The greater the value of α is, the higher the probability of covering the load demand is. The greater the value of β is, the higher the probability of covering the load demand using energy stored in the batteries is. At every iteration α and β are compared to randomly generated values within the (0,1) interval, thus defining 3 methods of generating new solutions:

- one for very low load demands;
- one where the load demand is covered using the microgrid elements in order of their operating costs;
- one where the load demand is covered mostly using energy stored in the batteries.

For the second method the new value of the decision variable is obtained as follows:

$$X_i = r \cdot X_{i \max} \quad (9)$$

where r is a randomly generated variable in the [0,1) interval, and $X_{i \max}$ is the maximum value of the decision variable.

The developed optimization method is a combination of dynamic and stochastic programming. Given that the optimization problem can be instinctively divided into 24 subproblems, one for each time slot, dynamic programming is a natural solution to solve it. On the other hand, in order to obtain the variety of solutions offered by stochastic methods and to avoid solving a complicated system of equations, variables whose values are randomly generated are used to obtain possible new solutions.

Table 2 represents the centralization of the daily operating costs obtained using the MILP method and the 3 optimization methods implemented in this thesis. As one can see, the lowest operating costs were obtained using the SD optimization method.

Table 2. Daily operating costs obtained for each month of the year [€]

Month	MILP	HS	PSO	SD
January	0.83368	0.563176	0.516328	0.3012
February	0.7827	0.557368	0.512108	0.390692
March	0.73028	0.55368	0.477628	0.307324
April	0.62064	0.579932	0.477668	0.285776
May	0.37621	0.240036	0.371468	0.174164
June	0.22219	0.19902	0.327112	0.176388
July	0.20558	0.189248	0.36526	0.089004
August	0.35763	0.172988	0.384388	0.169404
September	0.62907	0.499768	0.453308	0.322304
October	0.74412	0.616192	0.480848	0.343924
November	0.81262	0.657828	0.508488	0.378004
December	0.9108	0.575764	0.522108	0.26892

Chapter 7 refers to the simulation of the 3 optimization methods, the experimental validation of the SD optimization method and the implementation of the real-time control method of the microgrid.

A Model in the Loop simulation was used to validate the solutions generated by the optimization methods. The MATLAB / Simulink model of the proposed microgrid includes all of its elements and is illustrated in Figure 2.

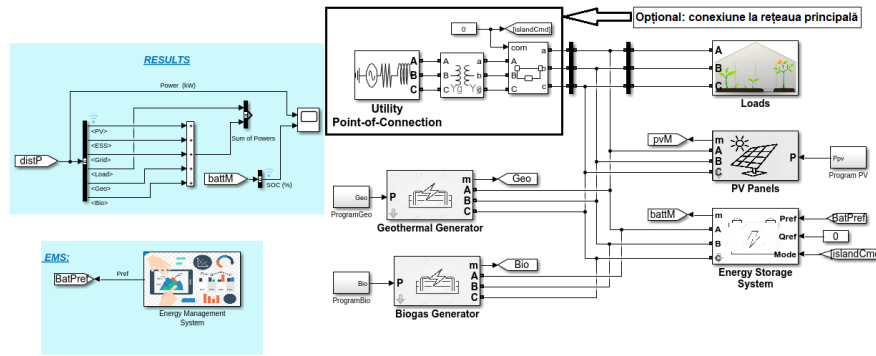


Figure 2. The model of the proposed microgrid

The operating schedules generated by the 3 optimization methods for a day in October were simulated. For each solution, the calculated SoC values and those obtained during the simulation were compared in order to determine which solution has the best performance. Each simulation provides two graphs: the first illustrates the power generated and the load demand, and the second illustrates the variation of the SoC over the simulated 24 hours. Tables 3-5 below compare the results obtained by calculations with those obtained by simulation for the solutions of the 3 optimization methods. As one can see, the smallest differences between calculations and simulations were obtained for the solution offered by the SD method. The biggest differences appear in the solution offered by the HS method.

Table 3. SoC values comparison for the HS method [%]

	t=9	t=16	t=24
Calculated SoC	88.9417	96.2583	95.1583
Simulated SoC	89.74	96.69	97.09
Difference	0.7983	0.4317	1.9317

Table 4. SoC values comparison for the PSO method [%]

	t=9	t=16	t=24
Calculated SoC	93.93	100	97.508
Simulated SoC	93.58	98.72	97.86
Difference	0.35	1.28	1.9317

Table 5. SoC values comparison for the SD method [%]

	t=9	t=16	t=24
Calculated SoC	93.2917	93.2917	96.8167
Simulated SoC	93.08	93.05	96.82
Difference	0.2117	0.2417	0.0033

Using the simulations we can see that all 3 solutions are valid, but even if small differences between calculations and simulations are expected, large differences between the two mean that the solution generated by the optimization method is not ideal in terms of equipment wear even if it is mathematically correct and respects the set of constraints of the optimization problem.

Given that the SD method generated better results than the other two optimization methods, it was decided to experimentally validate it. Figure 3 below illustrates the experimental microgrid.

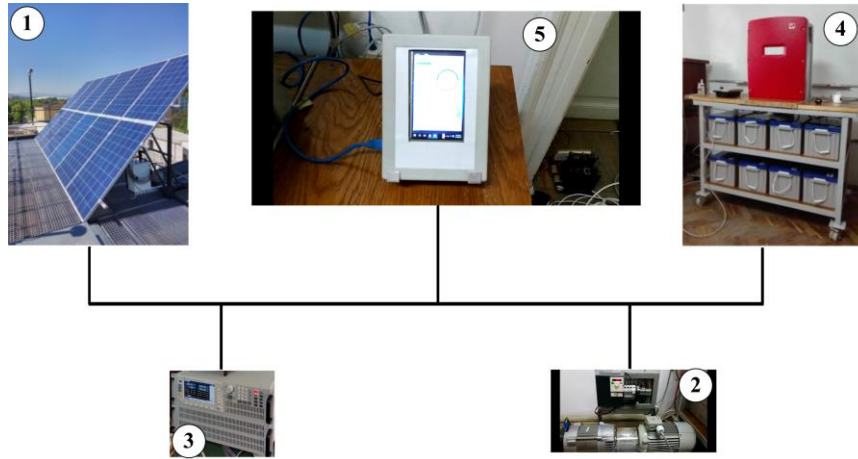


Figure 3. The experimental microgrid

Its components are as follow:

- (1) 12 250 W ET-Solar photovoltaic panels, connected to the microgrid using the 3.8 kW SMA Sunny Boy 3600TL-21 inverter;
- (2) an emulator for the geothermal generator with a maximum output of 1 kW;
- (3) an electronic load;
- (4) an energy storage system consisting of 8 12V, 200 Ah VRLA batteries, connected to the microgrid using the SMA Sunny Island 6.0H inverter, with a 19.2 kWh capacity;
- (5) an energy management system.

The differences between the experimental and the proposed microgrids areas follow:

- the reduced maximum output of the geothermal generator emulator;
- the unavailability of the biogas generator emulator;
- the reduced capacity of the energy storage system;
- different generation profile for the photovoltaic panels due to the different location.

Given the differences above, modifications to the optimization problem, optimization method, and simulation model were required for experimental validation. In addition, the experimental validation of the SD method involved the comparison of the results obtained using it with those obtained using an energy management algorithm based on SoC, previously developed and implemented for the same microgrid. Due to the limitations of day-ahead scheduling methods, namely the fact that they are based on meteorological and load demand predictions, the development of an accelerated testing method was necessary in order to compare the performances of the two methods. The correlation between the simulated time and the relevant durations from the two experiments are presented in Table 6.

Table 6. Correlation between the simulated time and the relevant time intervals from the experiment

Simulation	Experiment
24 h	4 h
1 h	10 min
1 min	10 s

Firstly, the solution offered by the SD method was simulated for validation. Then the same solution was transformed for the accelerated test. After running the test on the experimental microgrid, the report generated by the energy management system was used to create graphs illustrating the power generated by the photovoltaic panels, the power generated by the geothermal generator emulator and the SoC variation. Figures 4, 6 and 8 below illustrate the results obtained using the simulation, and Figures 5, 7 and 9 those obtained during the experiment.

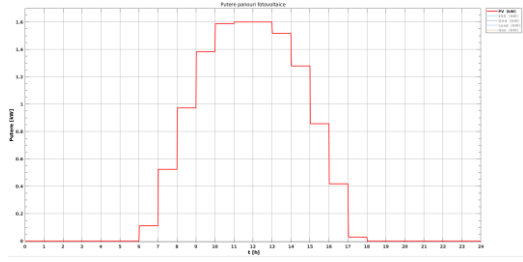


Figure 4. Power generated by the photovoltaic panels - simulation

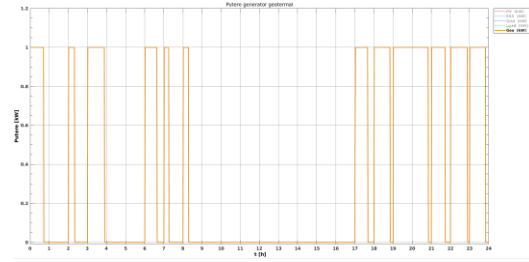


Figure 6. Power generated by the geothermal generator - simulation

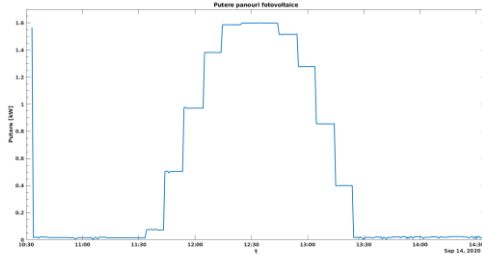


Figure 5. Power generated by the photovoltaic panels - experiment

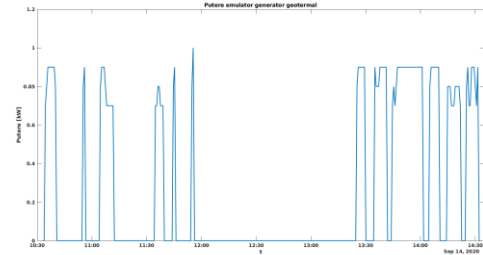


Figure 7. Power generated by the geothermal generator emulator - experiment

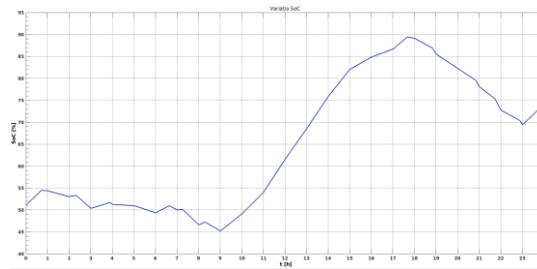


Figure 8. SoC values - simulation

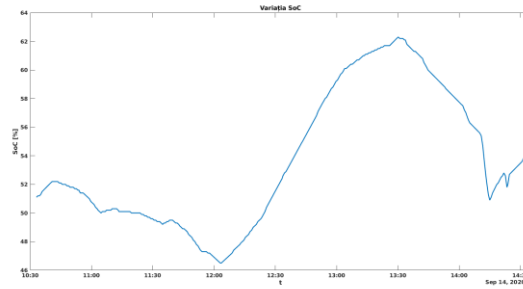


Figure 9. SoC values - experiment

We can see that the graphs obtained using the simulation and those obtained during the experiment have the same shape. The same generation profile of the photovoltaic panels and the same operating program of the generator / emulator were used. By comparing the SoC variation graphs we can conclude that the solution generated by the SD method is a valid one. The second stage of the experiment involved testing the SoC-based management algorithm under the same conditions (same photovoltaic panel generation profile and same load demand profile). Figures 10, 11 and 12 below illustrate the graphs obtained by processing the report generated by the energy management system after the second experiment.

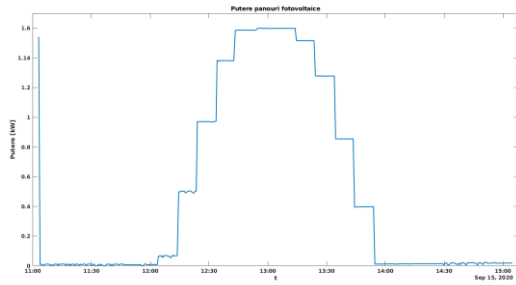


Figure 10. Power generated by the photovoltaic panels – second experiment

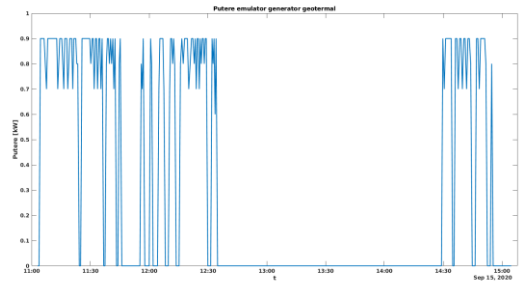


Figure 11. Power generated by the geothermal generator emulator – second experiment

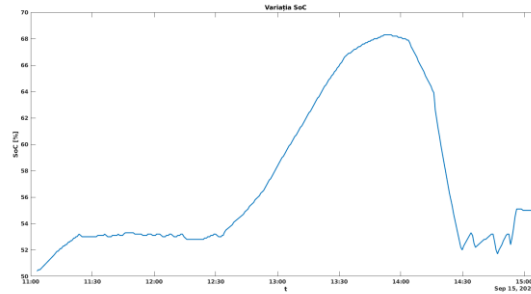


Figure 12. SoC values – second experiment

The conditions of the second experiment coincide with the conditions of the first. The table below represents the comparison of the operating costs obtained from the two experiments. These were calculated by scaling the data from the two reports over a 24-hour period and calculating the value of the objective function.

Table 7. Operating costs comparison

	SD method	Energy management algorithm	Difference
Minimum cost	-0.99 \$	-0.74 \$	0.25 \$
Maximum cost	-0.64 \$	-0.51 \$	0.13 \$
Average cost	-0.81 \$	-0.62 \$	0.19 \$

We can conclude that the use of a cost optimization method brings monetary benefits. The operating costs obtained are negative due to the charging of the batteries during the simulation and the two experiments. As per the objective function, charging the batteries decreases the operating cost of the microgrid.

The need to implement a real-time control method stems from the limitation of day-ahead scheduling methods. Consequently, the implemented control method follows the operating program generated by the SD method as a solution for the experimental microgrid as long as the simulated SoC values for each time interval remains within $\pm 2\%$ of the calculated one.

As one can see in Figure 13 below, the geothermal generator functions according to the schedule while the SoC value remains within the defined limits. If the SoC value is above the calculated one, the geothermal generator will be turned off. If the SoC value is below the calculated one the geothermal generator will be turned on.

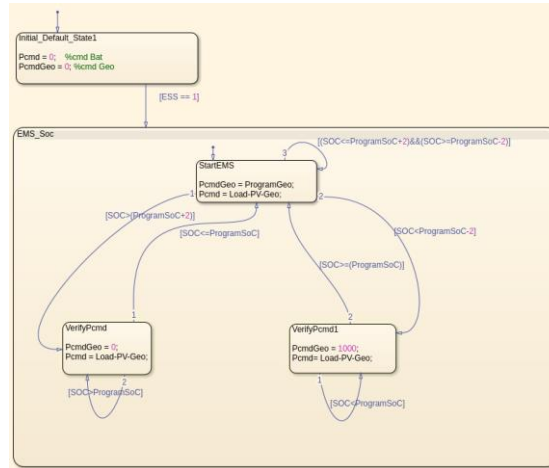


Figura 13. The decision logic of the real-time control method

In order to test the control method, 4 test scenarios were created. The first scenario is a control one, used to verify that the operating program is being followed. The second scenario is one in which the generation profile of photovoltaic panels has been modified. The third involved changes in the load demand profile. The fourth scenario introduced the changes made by the second and third ones. Figures 14-18 below illustrate the graphs of the generated power and load demand obtained by running the experimental microgrid simulation first without and then with the control method.

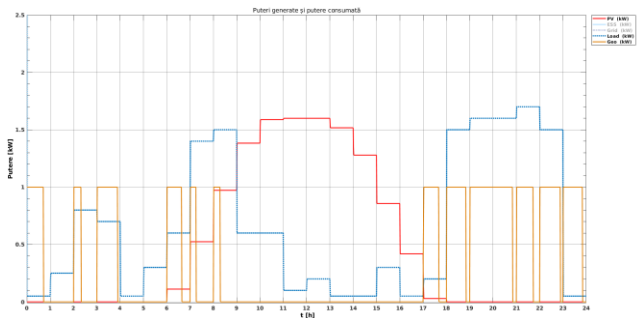


Figure 14. Simulation without the real-time control method

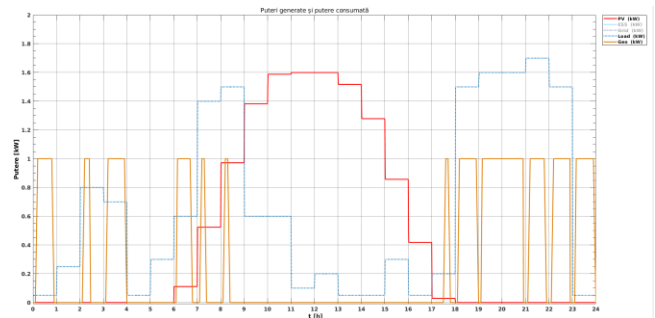


Figure 15. Control scenario simulation

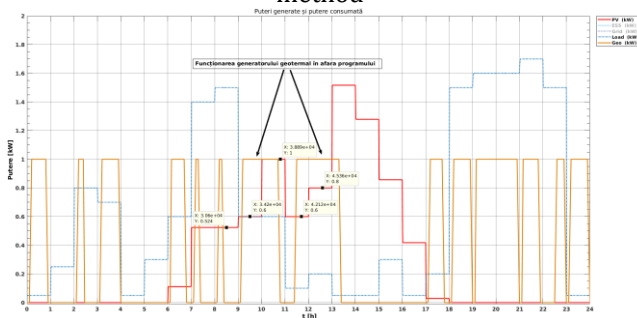


Figure 16. Second test scenario simulation

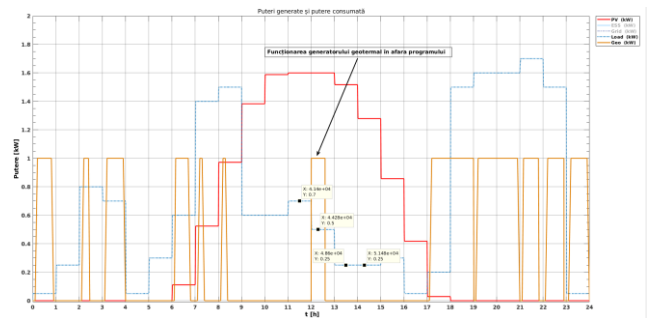


Figure 17. Third test scenario simulation

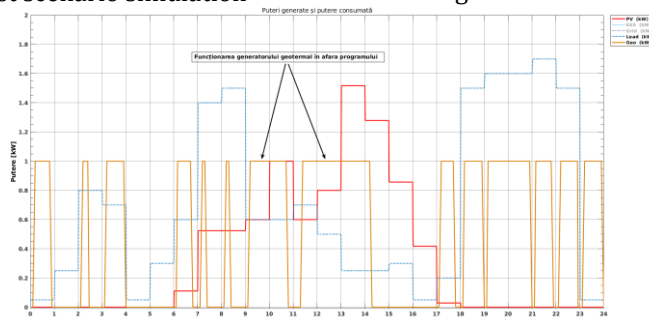


Figure 18. Fourth test scenario simulation

Figures 14 and 15 above illustrate the simulation of the same operating program, the first time without the control method and the second time with it. The generation profile of the photovoltaic panels and the load demand profile are identical. For this reason in Figure 15 the geothermal generator follows the operating program. In Figure 16 the cursors indicate the time intervals in which the generation profile of the photovoltaic panels has been changed. One can see the operation of the geothermal generator outside the program to cover the energy needs. Figure 17 illustrates the graphs of generated power and load demand for the third test scenario. Here the cursors indicate the time intervals in which the load profile has been changed. One can see the operation of the geothermal generator outside the program to cover the energy needs. Figure 18 shows the effect of cumulating the changes from the second and third scenarios. In this situation as well the energy needs are covered. By analyzing the figures above we can conclude that the control implemented method compensates for the differences between the two predictions and the simulated scenarios. The table below shows the SoC values obtained during the 5 simulations.

Tabelul 8. Comparația valorilor SoC obținute prin cele 5 simulări

t	Fără metodă de control	Scenariul de control	Cel de-al doilea scenariu de test	Cel de-al treilea scenariu de test	Cel de-al patrulea scenariu de test
1	54,49	54,63	54,63	54,63	54,63
2	53,14	53,39	53,39	53,39	53,39
3	50,52	50,72	50,72	50,72	50,72
4	51,4	51,31	51,31	51,31	51,31
5	51,1	51,04	51,04	51,04	51,04
6	49,48	49,55	49,55	49,55	49,55
7	50,14	50,45	50,45	50,45	50,45
8	46,74	47,1	47,1	47,1	47,1
9	45,35	45,48	43,1	45,48	43,1
10	49,2	49,67	48,06	49,67	48,06
11	54,14	55,02	52,39	55,02	52,39
12	61,61	63,14	59,44	59,91	56,22
13	68,62	70,74	68,12	69,09	63,26
14	75,95	78,69	78,21	76,23	75,78
15	82,11	85,37	84,89	82,09	83,81
16	84,92	88,42	87,94	85,14	86,86
17	86,77	90,43	89,94	87,15	88,87
18	89,24	90,67	92,32	89,52	91,25
19	85,69	87,22	88,96	86,16	87,88
20	82,39	83,44	85,17	83,16	84,1
21	78,27	80,44	82,17	80,16	81,1
22	72,94	75,66	75,18	74,8	76,32
23	69,59	72,15	71,67	71,12	72,81
24	73,44	76,17	75,89	75,13	76,99

By analysing the data from Table 8 one can draw the following conclusions:

- The SoC values from the control scenario are very close to the ones obtained by simulating the operating scenario without the control method;
- For the first 8 intervals the SoC values obtained during the 4 test scenarios are identical because no modifications were made in those intervals and, therefore, the operating scenario was followed;
- For the intervals corresponding to $t = 9, 10$ and 11 the values from the second and fourth scenarios are identical due to the fact that the generation scenario of the

photovoltaic panels was modified during those intervals, demonstrating that the same control method was used;

- For the second, third and fourth tests the greatest differences between them and the control test appear during the intervals corresponding to $t = 9 - 13$, when the modifications were made; in all three cases one can see that the control method compensated for those differences;
- The differences between the SoC values obtained for the last interval in all four test scenarios are very small.

The obtained simulation time is 6 - 10 seconds, and the computer used for simulations has the following specifications:

- CPU: Intel(R) Core(TM) i7-4720HQ CPU @ 260 GHz (1 physical processor, 4 cores, 8 threads);
- RAM memory: 16 GB;
- Operating system: Ubuntu 20.04.1 LTS.

Chapter 8 presents the conclusion and the personal contributions.

5. Personal contributions

The personal contributions brought by this thesis are:

1. Mathematical formulation of the optimization problem, highlighting the differences between equations and reality.
2. Defining the purpose of optimizing the operating cost of the microgrid and its limitations.
3. Implementing the harmony search method for the defined optimization problem.
4. Analysis of the solutions generated by the HS method and their correction to ensure their viability.
5. Identifying the cases where the solutions generated by the HS method, although correct, are not ideal.
6. Implementing the particle swarm optimization method for the defined optimization problem.
7. Analyzing the solutions generated by the PSO method and their correction to ensure their viability.
8. Identifying the cases in which the solutions generated by the PSO method, although correct, are not ideal.
9. Identifying the cases in which the general optimization methods used have imposed difficulties.
10. Proposing, developing and implementing a personalized optimization method that offers the advantages of general methods and avoids their disadvantages.
11. Demonstrating that the proposed goals for the SD method were achieved by comparing the results obtained using it with those obtained using the general optimization methods presented earlier.
12. Creating a simulation model for the proposed microgrid.
13. Adapting the results of the optimization methods in order for them to be simulated.
14. Simulating the results of the 3 optimization methods and demonstrating the efficiency of the personalized optimization method by analyzing the obtained results.
15. Developing a testing methodology for the experimental validation of the SD optimization method.

16. Adapting the optimization problem, the optimization method and the simulation model for the experimental microgrid.
17. Simulating the experimental microgrid together with the new form of the optimization method.
18. Experimental validation of the SD optimization method.
19. Demonstrating the usefulness of the cost optimization method by comparing the results obtained experimentally with those obtained by testing the same scenario using an energy management algorithm based on State of Charge.
20. Development and simulation of a real-time control method of the microgrid.

6. Future work

The directions in which this work can be continued are:

1. Development of new methods to optimize the operating cost, a possible direction due to the lack of a solution that cannot be improved (at the moment).
2. Adding optimization objectives to the problem, such as increasing battery life.
3. Defining the problem for a grid-connected microgrid and optimizing the cost to maximize profit.
4. Development of Real-Time Scheduling methods based on cost optimization.

7. List of publications

WOS papers:

- E. Lazar, A. Ignat, D. Petreus and R. Etz, "Energy Management for an Islanded Microgrid Based on Harmony Search Algorithm," 2018 41st International Spring Seminar on Electronics Technology (ISSE), Zlatibor, 2018, pp. 1-6, doi: 10.1109/ISSE.2018.8443673.
- A. Ignat, E. Lazar and D. Petreus, "Energy Management for an Islanded Microgrid Based on Particle Swarm Optimization," 2018 IEEE 24th International Symposium for Design and Technology in Electronic Packaging (SIITME), Iasi, 2018, pp. 213-216, doi: 10.1109/SIITME.2018.8599272.
- A. Ignat, E. Lazar and D. Petreus, "Real-Time Scheduling for an Islanded Microgrid," 2019 IEEE 25th International Symposium for Design and Technology in Electronic Packaging (SIITME), Cluj-Napoca, Romania, 2019, pp. 351-354, doi: 10.1109/SIITME47687.2019.8990861.
- A. Ignat, D. Petreus and E. Lazar, "Cost Optimization and Day-Ahead Scheduling for a Renewable Energy Microgrid," 2019 42nd International Spring Seminar on Electronics Technology (ISSE), Wroclaw, Poland, 2019, pp. 1-6, doi: 10.1109/ISSE.2019.8810290.
- A. Ignat, E. Szilagyi and D. Petreus, "Renewable Energy Microgrid Model using MATLAB — Simulink," 2020 43rd International Spring Seminar on Electronics Technology (ISSE), Demanovska Valley, Slovakia, 2020, pp. 1-6, doi: 10.1109/ISSE49702.2020.9120923.

BDI(IEEE) papers:

- A. Ignat, E. Szilagyi and D. Petreus, "Islanded Microgrid Simulation and Cost Optimisation," 2020 IEEE 26th International Symposium for Design and Technology in Electronic Packaging (SIITME), Pitesti, Romania, 2020, pp. 426-429, doi: 10.1109/SIITME50350.2020.9292153.

Papers submitted for evaluation:

- A. Ignat, E. Szilagyi and D. Petreus, "Day-Ahead Scheduling, Simulation, and Real-Time Control of an Islanded Microgrid" – Advances in Electrical and Computer Engineering (AECE).