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A MPC Strategy for the Optimal Management of Microgrids Based on Evolutionary Optimization

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Abstract: In this paper, a novel model predictive control strategy, with a 24-h prediction horizon, is proposed to reduce the operational cost of microgrids. To overcome the complexity of the optimization problems arising from the operation of the microgrid at each step, an adaptive evolutionary strategy with a satisfactory trade-off between exploration and exploitation capabilities was added to the model predictive control. The proposed strategy was evaluated using a representative microgrid that includes a wind turbine, a photovoltaic plant, a microturbine, a diesel engine, and an energy storage system. The achieved results demonstrate the validity of the proposed approach, outperforming a global scheduling planner-based on a genetic algorithm by 14.2% in terms of operational cost. In addition, the proposed approach also better manages the use of the energy storage system.

Keywords: microgrid; model predictive control; evolutionary optimization; genetic algorithm

1. Introduction

The rapid growth of energy demand during the last few years [1], along with the increase of greenhouse gas emissions, and the exhaustion of fossil fuels [2], have motivated a gradual transition to more sustainable models. These new models are expected to be essential in the coming years [3]. Consequently, the energy sector is transforming its traditional paradigm, based on centralized grids with large and controllable generation units into a distributed model, which is strongly characterized by the integration of renewable energy systems (RES) [4].

In this new paradigm, microgrids (MGs) play a fundamental role [5]. MGs can be defined as low-voltage distribution grids composed of several elements, such as RES, controllable auxiliary energy sources, like thermal engines, energy storage systems (ESSs), and controllable loads [6]. This scheme permits a better integration of these elements into the grid, not only improving their reliability but also reducing the dependence on fossil fuels [7]. In addition, MGs are envisioned to boost the penetration of electric vehicle technology [8].

In operation, MGs can work by being either connected to the grid and/or in isolated mode [9]. In the former, a MG is connected to the main grid, which manages the voltage and frequency control for guaranteeing the high reliability of modern national grids. In that scenario, MGs are responsible for optimizing the energy management by injecting and extracting energy from the main grid during high and low energy cost periods, respectively [10]. In addition, MGs allow an effective method of connecting RESs to the grid, which can maximize their efficiency [11].

Energy management systems (EMSs) constitute a fundamental component of the control architecture of a MG, being a matter of deep study in the literature [10,12,13]. EMSs consist of a set of tools used to monitor, control, and optimize the performance of the generation and transmission systems. Among the EMSs techniques, the unit commitment (UC) should be highlighted [14]. The UC technique is applied to MGs with the aim of optimizing the operation of the controllable generation units, which dispatch the active power and control the loads in accordance to a certain economic criterion [15]. The uncertainty of RESs and the presence of ESS make the UC a stochastic problem [16].

This work presents the application of a model predictive control (MPC) strategy with an evolutionary algorithm as the optimization engine to find the optimal energy management strategy of the UC problem in a MG. MPC is one of the paradigms par excellence of advanced control [17]. A MPC controller solves a real-time optimization problem to obtain the best solution of inputs (the sequence of control actions) so as to achieve a certain purpose (tracking of control variables, disturbance rejection, etc.). For this, the MPC uses a dynamic model of the system to predict the future evolution of the variables within a prediction time (prediction horizon). It is an optimal control scheme with a rolling (or receding) horizon (RH) [18–20]. The MPC only applies the first step of the sequence of optimal control actions and, for the following sample, recalculates the optimization, moving the time horizon forward, after obtaining the feedback of the measured variables. Therefore, MPC is based on the update of the optimal decision on the basis of the most recent information. In this case, the MPC will define a future prediction horizon to determine the optimal control signals (power provided or consumed) for each element of the MG to reduce the overall operational cost. At each step, the MPC strategy should solve several complex optimization problems related to the optimal control signal and the prediction horizon considered. Therefore in this work, the use of an evolutionary algorithm, like a genetic algorithm, is proposed to optimize the control signals of the MPC so as to overcome the non-linearity and non-convexity of the optimization problems arising from the operational cost model of a MG. In this work, a hybrid MG is considered, which is composed of: A wind turbine (WT), PhotoVoltaic plant (PV), diesel engine (DE), and micro-turbine (MT), in addition to an ESS.

The main contributions of this work are:

- A novel real-time MPC strategy is used to manage the control of a MG where an evolutionary technique is used as optimization engine in order to overcome the complexity of the optimization problems;
- The validation of the proposed approach and comparison with other scheduling techniques that do not follow the future horizon prediction of the MPC strategy to control the operation of a MG.

2. Related Work

The application of the UC problem to manage a MG in an optimal way constitutes an extensively discussed topic in the literature [16,21–23]. In this framework, the UC problem can be applied by considering a wide range of different objective functions and optimization methods, such as linear programming (LP), non-linear programming (NLP), stochastic programming (SP), dynamic programming (DP), non-differential programming (NDP), and MPC [12,24]. Regarding these approaches for solving the resultant problem, the most used strategies include heuristic methods, neural networks, and round robbin, as well as the Gauss Seidel, and SD Riccati equation [12,24].

Although the MPC constitutes well known techniques in the process industry, the use of MPC to optimize the operation of a MG in an optimal way has only gradually gained interest in the area of power systems during the last few years [25]. A MPC strategy can be found in different works to solve the optimization problem formulated as a MILP. For instance, authors in [26] present a stochastic MILP model, which is applied to study the impact of strong wind penetration in the electric system of Ireland. On this line, authors in [18] use a MPC strategy to minimize the fuel consumption in a MG that includes PV systems, WT, a DE, ESSs, and several loads, including a controllable water supply system. This problem is applied using forecast models, in order to provide a 48-h horizon of prediction.

In [20], an objective function is proposed to maximize the benefit, by considering flexible demand profiles and punishing terms. A RH approach is used to deal with the uncertainty associated to RES generation and load consumption. Moreover, some other authors use an algorithm based on RH to find the optimal performance of a battery energy system storage (BESS) in MGs (see for instance [27,28]). Similarly, the research done in [29] lies in using a MPC to minimize the operation costs of a MG which operates connected to the grid, while satisfying the predicted demand during a certain time period in an efficient way. The mathematical problem was formulated as a MILP. The authors developed a set of simulations to compare different control strategies (heuristic, MILP, and MPC-MILP) within a 24-h horizon, without considering demand forecast errors. The results demonstrated that a MPC-MILP strategy without storage led to a more efficient management of the MG and a higher level of energy sold to the main grid. Nevertheless, the consideration of storage provides a more economically efficient MG.

Computational intelligence can also be used to design big-scale MPC-based control strategies. In this context, the use of evolutionary algorithms as the solving tool is gaining relevance in many scientific fields, including energy management. An illustrative example of this can be found in [30], where a MPC controller to the attitude control of a geostationary flexible satellite is tuned by using a GA. In [31] the authors propose a GA to optimize the water distribution in the city of Chojnice. Authors in [32] present the use of multi-objective and interactive GAs for the weight tuning of a MPC-based algorithm. In [33] a particle swarm optimization (PSO) algorithm is proposed to improve the system response of the three-phase separator used to separate well crude into three portions: Water, oil, and gas. In [34], fuzzy logic is applied to model the controlled process. In this work, a GA is used to optimally adjust the MPC parameters, resulting in a method which is applicable to multiple-input multiple-output (MIMO) systems with input and output constraints. Regarding the energy management in MGs, the following works are of particular relevance. In [35], the authors propose a MPC to optimize the energy consumption of a building, by using a 24-h horizon under a set of assumptions related to the demand forecast, maximum power, cost, etc. To this end, a multi-objective genetic algorithm (MO-GA) is proposed to reduce the search space. In [36], a MPC is proposed to study the interconnection of different MGs, each of which locally controls the ESS, active power balance, and power flow within the external grid and other MGs. To this end a PSO algorithm is proposed [37].

This work is a step forward with respect to previous works [38], where a 24-h offline planner was designed using an evolutionary approach. Thus, a novel MPC strategy is used to manage the uncertainty and errors made in power demand forecasting. The MPC defines a window prediction horizon that enables a fine tuning re-scheduling of the control signals that adapt better to the real power demand, and consequently, reduce the overall operating cost of the MG. The proposed approach defines a real-time control of the MG. The proposed evolutionary algorithm presents a good trade-off between the exploration and exploitation capabilities due to the fact that several probabilities are used by the genetic operators during the execution.

3. Introduction to the Problem

This section describes the power system under consideration in this study as well as the problem to be solved.

3.1. System Definition

Traditional power systems have a top-down operated architecture in which their components can be broadly classified as: Generators that supply the electric power, the transmission system that carries the power to the load centers, and the distribution system that feeds the loads. This paradigm is now being altered by the integration of distributed energy resources and the emergence of a new figure called prosumer, that is, agents at the electricity grid that can both consume and produce power.

This change in the traditional power system scheme introduces new challenges to the scientific community that can be partially addressed by the use of MGs. A MG is a solution for the reliable integration of distributed energy resources, including ESSs and controllable loads [39].

MGs found in the literature can largely vary their architecture, normally including RES, controllable generation units, and ESS, being able to operate either connected to the grid, isolated, or both. In addition, MGs can interconnect to each other to create a new grid with an improved performance. Thus, let us consider the MG that is depicted in Figure 1 and that has been previously studied in [38]. This MG is composed by two dispatchable units, two renewable energy resources, and an ESS. The dispatchable units considered are a diesel engine (DE) and a microturbine (MT). In regards with the renewable energy resources, a wind turbine and a photovoltaic system are taken into account.

Figure 1. A MG (microgrid) considered in the problem, consisting of (**1**) a wind turbine, (**2**) photo-voltaic panels, (**3**) a microturbine, (**4**) a diesel engine, (**5**) an ESS (energy storage system), and (**6**) the demand.

In the following subsections, the different components of the MG will be defined together with information about its operation and peculiarities.

3.2. Problem Description

The aim of this paper is to present a real-time algorithm to optimally operate a MG. To this end, the factors enumerated next will be considered:

1. The operation and maintenance of the distributed generation units are different according to their type and design. The constraints associated to each of them must be studied. Section 4 presents detailed models of each of the components of the MG;
2. The energy provided by the renewable resources is directly affected by the meteorological conditions. Although these conditions can be estimated, the uncertainty in the estimation is an important factor that must be incorporated in the problem;
3. Discussion about the meaning of optimal operation of a MG. There are several works that study this issue, and most of them agree that the optimal operation of a MG implies the provision of a robust service, with minimal operational cost. This concern will be tackled in Section 4.

Based on the aforementioned considerations, a proposed solution is introduced in Section 5 and evaluated under simulation in Section 6.

4. System Modeling

This section presents the models used for each component of the MG under consideration. These models and their limitations will define the constraints of the final cost function.

4.1. Demand and Renewable Generation Forecasting

The inherent variability of solar and wind generation at higher grid penetration levels poses problems associated with the network reliability. As a result, robust control methods [40] or accurate forecast systems [41,42] are required in order to ensure the secure and reliable operation of the grid.

Furthermore, the demand is also subject to uncertainties. However, this issue has been studied over decades and more accurate estimators have been developed [43].

In this paper it is considered that both, renewable energy generation and demand are estimated by using an ARMA model trained with historical data. The ARMA model that is used in this paper is the one previously presented by the authors in [15]. In order to know the accuracy of the method, some simulations are run and the results are compared with known historical data. After that, the error is fitted to a normal distribution $\mathcal{N}(\mu, \sigma)$. Thus, the generated power and the demand can be expressed as:

$$\begin{aligned} P_{DE,t} &= \hat{P}_{DE,t} + \tilde{e}_{DE,t}, \quad \forall t,\ \tilde{e}_{DE,t} \sim \mathcal{N}(0, \sigma_{DE,t}), \\ P_{MT,t} &= \hat{P}_{MT,t} + \tilde{e}_{MT}, \quad \forall t,\ \tilde{e}_{MT} \sim \mathcal{N}(0, \sigma_{MT,t}), \\ P_{DM,t} &= \hat{P}_{DM,t} + \tilde{e}_{DM,t}, \quad \forall t,\ \tilde{e}_{DM,t} \sim \mathcal{N}(0, \sigma_{DM,t}), \end{aligned}$$

where $P_{DE,t}$, $P_{MT,t}$, and $P_{DM,t}$ are the power generated by the DE and the MT and the power demanded in the MG at time t, respectively; $\hat{P}$ denotes the power forecasting using the ARMA model; and $\tilde{e}_{DE,t}$, $\tilde{e}_{MT,t}$ and $\tilde{e}_{DM,t}$ are, respectively, the estimation error of the power produced by the DE and the MT and the demanded by the load at time t.

Figure 2 shows a set of 24 h data regarding wind and photovoltaic generation and the power demanded in the MG. In addition, the corresponding estimation for each one of the powers is also depicted.

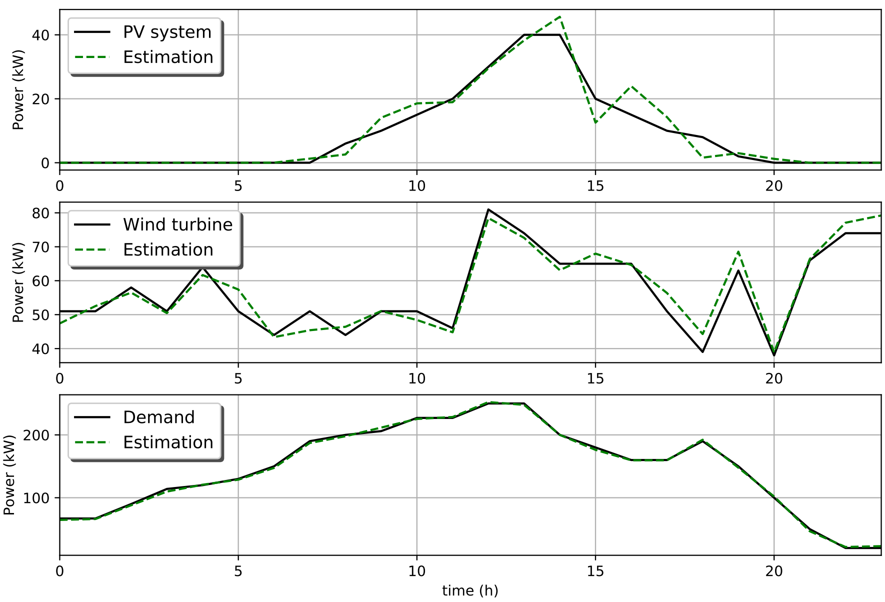

Figure 2. ARMA model estimation of the renewable units generation and the power demanded in the MG for a short time window of 24 h.

4.2. Diesel Engine and Micro-Turbine Models

The aim of economic dispatch is to minimize the fuel consumption of the generators or the operating cost of the whole MG by determining the power output of each unit under the constraint condition of the system load demands.

The overall cost of the generation units considered in the present problem involves fuel consumption, labor, maintenance, and fuel transport costs. In order to build up a cost term in the objective function considering all these factors, the costs are included as a fixed portion of the operating cost. The cost function of these units is widely expressed as a quadratic function with the following shape [44]:

$$C_{DE,t} = d_{DE} + e_{DE}P_{DE,t} + f_{DE,t}P_{DE,t}^2, \quad \forall t, \tag{1}$$
$$C_{MT,t} = d_{MT} + e_{MT}P_{MT,t} + f_{MT,t}P_{MT,t}^2, \quad \forall t, \tag{2}$$

where $P_{DE,t}$ and $P_{MT,t}$ are the power generated by the DE and the MT at ime t, respectively; $C_{DE,t}$ and $C_{MT,t}$ are the total cost of operation of the generators; and the rest of the parameters are known coefficients that depends on the type of generator.

In addition to the previous cost, the start-up of these generators has an associated cost that can be approximated by the following expression [45]:

$$C_{DE,t}^{start-up} = a_{DE} + b_{DE}\left[1 - exp\left(\frac{T_{DE,t}}{c_{DE}}\right)\right], \tag{3}$$
$$C_{MT,t}^{start-up} = a_{MT} + b_{MT}\left[1 - exp\left(\frac{T_{MT,t}}{c_{MT}}\right)\right], \tag{4}$$

where a_{DE} and a_{MT} are the hot start-up costs, b_{DE} and b_{MT} are the cold start-up costs, c_{DE} and c_{MT} are the unit cooling time constant, and $T_{DE,t}$ and $T_{MT,t}$ represent the time previous up to t that each unit has been off. Note how the start-up cost of the generators increases with the time that it has been off.

The power output given by the dispatchable generator is limited by the minimal and maximal capacity of the generating unit, that is:

$$\underline{P}_{DE} \leq P_{DE,t} \leq \overline{P}_{DE}, \quad \forall t, \tag{5}$$
$$\underline{P}_{MT} \leq P_{MT,t} \leq \overline{P}_{MT}, \quad \forall t, \tag{6}$$

where $\underline{P}_{DE}$, $\underline{P}_{MT}$ and $\overline{P}_{DE}$, $\overline{P}_{MT}$ are the lower and upper limits of the generating power of each dispatchable unit.

4.3. Energy Storage System

In recent years, several forms of storage energy have been deeply studied. Examples of them are electrochemical batteries, supercapacitors, compressed air energy storage, or flywheel energy storage. In this work a Lithium ion battery was selected. The main reason is that they provide good properties, such as the energy-to-weight ratio, no memory effect, and the low loss of charge when it is not used [46].

The model adopted for the ESS is characterized by three main parameters:

- The capacity of the battery that defines the maximum amount of energy that can be stored;
- The maximum charging and discharging rates of the ESS;
- The maximum depth of discharge that indicates the percentage of the battery that can be discharged related to the overall capacity.

Therefore, based on the above parameters, it can be defined the state of charge of the battery, SoC_t, as the energy storage in the battery at a certain time instant. The maximum and the minimum value of this parameter is bounded:

$$\underline{SoC} \leq SoC_t \leq \overline{SoC}, \quad \forall t, \tag{7}$$

where $\overline{SoC}$ is the capacity of the battery and $\underline{SoC}$ is given by the maximum depth of discharge.

The state of charge is a dynamic state that evolves based on the power flow at the ESS terminals. In particular, the dynamics of the battery is modeled by the following equation:

$$SoC_{t+1} = SoC_t - \begin{cases} P_{ESS,t}\Delta t \eta_c & \text{if} \quad P_{ESS,t} < 0, \\ P_{ESS,t}\frac{\Delta t}{\eta_d} & \text{if} \quad P_{ESS,t} > 0, \end{cases} \tag{8}$$

where $P_{ESS,t}$ represents the power given or requested by the battery and η_c and η_d are, respectively, the charging and discharging efficiency of the system. Note how $P_{ESS,t}$ can be both, positive or negative, depending on whether the battery is discharging or charging. Moreover, the following restriction should be met:

$$\underline{P}_{ESS} \leq P_{ESS,t} \leq \overline{P}_{ESS}, \quad \forall t, \tag{9}$$

where $\underline{P}_{ESS} < 0$ and $\overline{P}_{ESS} > 0$ are, respectively, the lower and upper bounds of the power supplied or demanded by the battery.

4.4. Microgrid Parameters

This subsection describes the particular parameters used in the MG under study. Although other values can be considered, the values employed describe a representative scenario [15,38].

Figure 3 represents the start-up cost and the cost of operation of the dispatchable units. The parameters chosen for the terms in Equations (1)–(6) are summarized in Table 1.

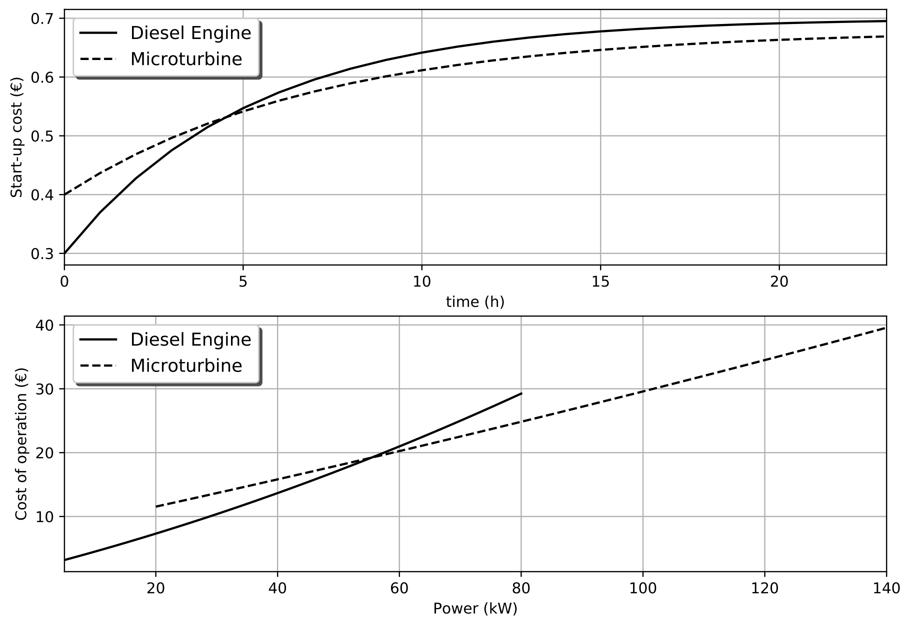

Figure 3. Start-up cost and cost of operation of the dispatchable units considered in the problem.

Table 1. Characteristic parameters of each of the generators considered in the MG.

i	$\underline{P}_i$ (kW)	$\overline{P}_i$ (kW)	d_i (€/h)	e_i (€/kW h)	f_i (€/kW^2 h)	a_i (€)	b_i (€)	c_i (€)
Diesel engine	5	80	1.9250	0.2455	0.0012	0.3	0.4	5.2
Microturbine	20	140	7.4344	0.2015	0.0002	0.4	0.28	7.1

Finally, the parameters considered for the ESS that fit Equations (7) and (8) are shown in Table 2.

Table 2. Characteristic parameters of each of the generators considered in the MG.

$\underline{P}_{ESS}$ (kW)	$\overline{P}_{ESS}$ (kW)	$\underline{SoC}$ (kWh)	$\overline{SoC}$ (kWh)	η_c	η_d
−120	120	70	280	0.9	0.9

5. Operation Objective and Proposed Solution

The previous section presented the operational constraints of the problem together with some cost terms regarding the dispatchable units that must be taken into consideration. This section presents the operation policy that will be followed in order to optimally operate the MG. The main aim of the algorithm is to minimize the overall cost of operation of the MG (expressions in Equations (1)–(4)) for an operating time of 24 h. This work proposes a MPC strategy with an evolutionary approach as an optimization tool for minimizing the operation cost of the MG under study during a period of 24 h. We divide this section into two parts, first, the MPC technique is described, and second, the evolutionary approach used as an optimization engine is detailed.

5.1. Model Predictive Control

In general, a MPC-type controller calculates a sequence of control actions, solving a functional optimization problem in a future time horizon, at each sampling time. As mentioned earlier, the objective is to minimize the total cost of the operation of the system, which will be the following summation:

$$\mathcal{J} = \sum_{k=0}^{N_p} \left(C_{DE,t+k} + C_{MT,t+k} + n_{DE,t+k} \cdot C_{DE,t+k}^{start-up} + n_{MT,t+k} \cdot C_{MT,t+k}^{start-up} \right) \tag{10}$$

where N_p is the prediction horizon and t the actual time. The variables n_{DE} and n_{MT} are discrete and take the value 1 when the corresponding unit starts at that time and 0 when it continues running or stopped with respect to the previous sampling time. Notice that Equation (10) is clearly a non linear cost function, including quadratic and exponential terms. Therefore, the minimization of such expression can suffer from local minimum using traditional solvers. Taking into account the constraints Equations (5)–(9), and the demand coverage, the MPC problem can be formulated as follows:

$$\begin{aligned}
&\min_{\mathbf{u}} \left\{ \mathcal{J}(\mathbf{u}) \right\} \\
&\texttt{s.t.} \\
&\underline{P}_{DE} \leq P_{DE,t+k} \leq \overline{P}_{DE}, \\
&\underline{P}_{MT} \leq P_{MT,t+k} \leq \overline{P}_{MT}, \\
&\underline{SoC} \leq SoC_{t+k} \leq \overline{SoC}, \\
&SoC_{t+k+1} = SoC_{t+k} - \begin{cases} P_{ESS,t+k} \Delta t \eta_c & \text{if} \quad P_{ESS,t+k} < 0, \\ P_{ESS,t+k} \frac{\Delta t}{\eta_d} & \text{if} \quad P_{ESS,t+k} > 0, \end{cases} \\
&\underline{P}_{ESS} \leq P_{ESS,t+k} \leq \overline{P}_{ESS}, \\
&P_{DM,t+k} = P_{DE,t+k} + P_{MT,t+k} + P_{WT,t+k} + P_{PV,t+k} + P_{ESS,t+k}, \\
&\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad k \in [0, N_p]
\end{aligned} \tag{11}$$

where **u** is the sequence vector:

$$\mathbf{u} = [P_{DE,t+1}, ..., P_{DE,t+N_u}, P_{MT,t+1}, ..., P_{MT,t+N_u}, P_{ESS,t+1}, ..., P_{ESS,t+N_u}] \quad (12)$$

and N_u is the control horizon, that could be chosen such as $1 \leq N_u \leq Np$. As previously mentioned, after this calculation, only the first values of the sequences are used: $u_1 = [P_{DE,t+1}, P_{MT,t+1}, P_{ESS,t+1}]$, they are applied and everything is re-calculated in the following sampling time. This continuous feedback allows for a good controller performance, even with model errors. In fact, the stochastic nature of renewable energy production and demand makes MPC an appropriate strategy, comparing it with static planning through a single optimization. The problem posed in Equation (11) is a mixed integer nonlinear optimization. If the problem become non-convex, a huge computational effort may be required to obtain the solution. This is especially relevant when it comes to real-time optimization, as is the MPC. For this reason, we propose an evolutionary approach like a genetic algorithm (GA), which performs well in complex computational optimization problems like the one presented in Equation (11).

5.2. Evolutionary Based Optimization

Evolutionary algorithms are powerful optimization techniques for complex engineering problems [47]. The main idea behind a genetic algorithm is to evolve a set of potential solutions namely population through genetic operations, such as selection, crossover, and mutation. The potential solutions are coded in a chromosome-like structure. Normally, after a number of generations, the best solution for the problem is included in the final population. Although there are many variants of genetic algorithms, in this work a mupluslambda implementation is used, which has been proven to achieve significant results in similar problems [38].

In this work, each possible solution or individual represents the power provided by the MT and DE for the temporal window considered. The power of the ESS can be derived from the power balance. Notice that the renewable energy systems like PV and wind generation will always contribute to the power balance if possible since they are the cheapest power sources.

The objective function is given by minimizing Equation (10) for each step of the MPC-based approach subject to the constraints given by the maximum generation powers of the DE and MT such as Equations (5) and (6), and the constraints given by the battery, such as Equations (7) and (9). If a potential solution does not meet the aforementioned constraints, it will be penalized with a death penalty by assigning a very high value. Therefore, such a solution will not participate in the genetic operations. It is important to highlight that a different optimization problem should be solved at each step of the MPC-based proposed approach.

Regarding the genetic operators, the tournament selection mechanism is used since it has been demonstrated to achieve suitable results for a wide variety of scenarios. In each tournament, a group of individuals are randomly selected from the population that compete with each other to be chosen as a parent. Then, the best one is chosen as one of the parents to be used in crossover and mutation operations. A tournament size of three has been demonstrated to be suitable for problems with a moderate number of variables. With respect to the crossover operation, the two-point method has been used. The mutation scheme used is a tailored Gaussian mutation algorithm, where each variable can change according to a Gaussian distribution with mean μ and standard deviation σ. The variability of a given gene after mutation depends on the value of σ. This mutation scheme was proposed in [38] achieving satisfactory results.

Notice that the obtained results can vary significantly due to two main reasons. Firstly, the stochastic nature of the elements of the MG, specially the renewable sources and the demand forecasting. Secondly, the genetic operators of the GA that determine its exploration and exploitation features, such as crossover and mutation probabilities. To overcome such variability, the proposed approach run the GA multiple times with different configurations (crossover and mutation probabilities) to guarantee an exploration and exploitation trade-off.

6. Simulation Results

This section presents some simulations that validate the good performance of the algorithm. To achieve this purpose, the MG presented in Section 4.4 has been used and the power demand forecasting presented in Figure 2 is considered. First, the proposed approach settings considered to solve the problem are presented. After that, the optimal solution is shown and the results are discussed. Finally, the proposed strategy is compared with an offline schedule optimization previously presented by the authors in [38] and the most important features are discussed.

6.1. Proposed Approach Setting

The proposed MPC strategy uses a prediction horizon of 24 steps (1 day), increasing the prediction horizon above this value increases the computational complexity of the problem with little benefit. Note that the worldwide electricity market operators normally plan the electricity sell with a 24-h ahead policy. Therefore, as the proposed approach is aimed at reducing the operational cost of MGs, considering a 24-h prediction horizon of the MPC is suitable for including the power sources of the MGs to the market. In addition, we considered a high repetitiveness for the days. As shown in the results, the considered prediction horizon guarantees satisfactory results, reducing the operation cost of the MG with respect to a 24-h global scheduling as used in [38].

Table 3 contains the main configuration parameters used in the implemented GA. The algorithm has been implemented using the DEAP Python library [48] and the code is available at [49]. The crossover and mutation probabilities are used for five different runs out of the 15 simulations that were conducted at each step of the MPC strategy. Note that these values guaranteed a good trade-off between the exploration and exploitation capabilities of the genetic algorithm. Moreover, the value used for σ has been demonstrated in [38] to provide good results.

Table 3. Parameters of the GA (genetic algorithm).

Parameter	Value
λ	400
μ	400
Individuals	400
Generations	200
Selection	Tournament size = 3
Crossover	Two-point $p_{cx} = [0.6, 0.7, 0.8]$.
Mutation	Gaussian $p_m = [0.4, 0.3, 0.2]$, $\sigma = 30$.
Number of trials	15

6.2. Optimal Solution

Figure 4 represents the optimal power scheduling for all generators for a short time period of 24 h. Note that in this simulation, a MPC strategy with a prediction horizon of 24 time instants has been considered. Thus, every time a control action is applied that considers the measured demand and generation and the corresponding forecasting for the prediction horizon. In that way, the battery was optimally operated in order to guarantee a reliable operation of the MG. Notice that in the case of the battery, a positive power value means that it was providing energy and a negative value represents that it was charging in order to provide such energy later.

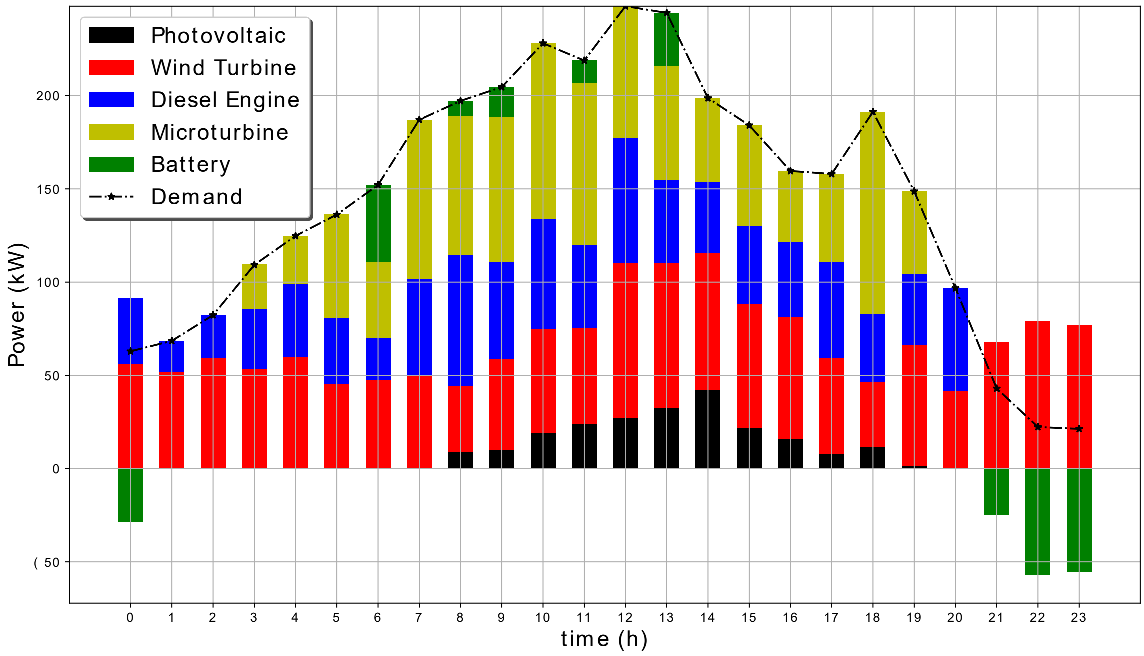

Figure 4. Optimal power scheduling for the time period considered.

The operation of the battery and its state of charge is depicted in Figure 5. As shown, the energy storage system supplied power during the peak hours of the day, relieving the generators from an operation close to the maximum power capability. Note that the battery was discharging from seven to 15 h, where higher power was demanded. Then, the battery remained at a minimum value until the demand was reduced at around 21 h. From 21 h until midnight, the battery was charging again. This optimal management of the battery system allowed an important reduction of the operation cost of the MG, according to the defined models of the MT and DE in Equations (1) and (2), where in both cases the cost raised quadratically with the power. Such an optimal management of the battery system is a consequence of the MPC strategy that intends to re-establish the state of charge of the battery before reaching the hours with a high demand of power for the following day.

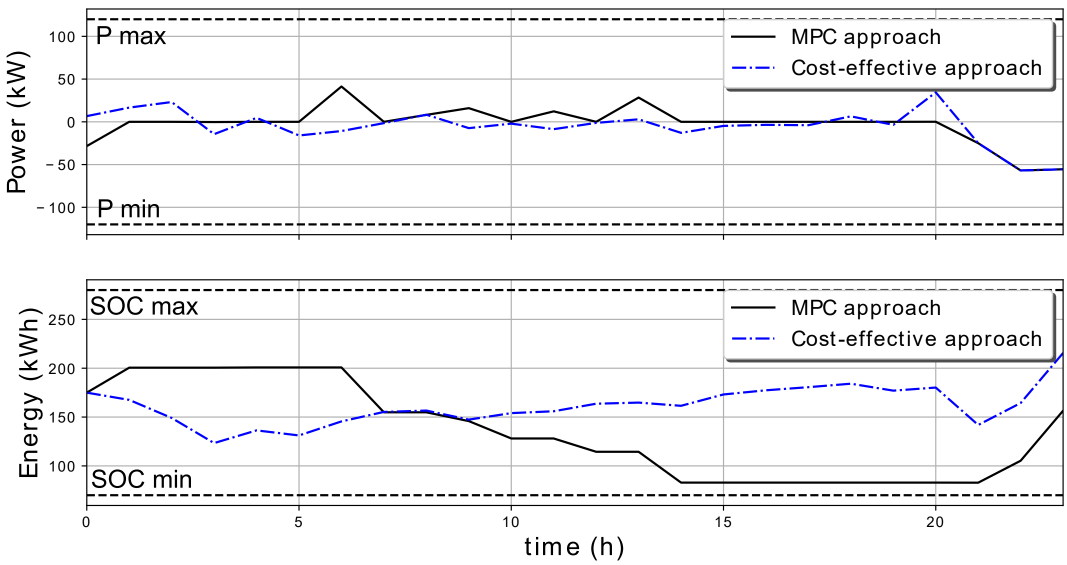

Figure 5. Optimal battery management for 24 h of operation for the two scenarios considered.

6.3. Comparison with 24-h Scheduling without the MPC Strategy

In this section the results obtained are compared with the ones presented in [38]. The result obtained there intend to minimize the same cost function as in the present work, however, in that scenario uncertainties in the power forecasting were not considered.

In order to compare the results, we ran the simulations and adjusted the power deviations due to the uncertainties with the energy storage system (in all the cases considered this was possible without violating restrictions). Table 4 collects the values of cost function Equation (10) particularized to each of the solutions. Note that in the case of the offline procedure proposed in [38] several trials have been considered to select the best results. However, in the present approach as it is a real-time method only one trial has been considered.

Table 4. Cost function value for each of the results considered.

Offline Approach	MPC-Based Approach
820.62	701.19

As shown, the high performance of the MPC approach is due to the fact that it adapted better to the problem at every time step and considered the error in power demand (see Figure 2). According to the results included in Table 4, the proposed approach outperformed the 24-h scheduling based on genetic algorithm by a 14.2% in terms of operational cost.

In addition, Figure 5 represents the state of charge of the battery and the power supplied/demanded from the MG for the two scenarios. As shown, the approach presented achieved a better use of the battery, taking advantage of its flexibility and moving to the extreme values of capability.

From the analysis of Figures 4–6, several important aspects can be derived. The power supplied by the battery in the proposed MPC-based approach increased during demand peaks with respect to the offline approach presented in [38]. This fact is significant in the interval period of 8 till 13 h, reaching values higher than 50 kW and a peak of 100 kW at 13 h, as it shown in Figure 4. This result corresponds with maximum energy values of 250 kWh stored by the battery system during the period 0 to 7 h (see Figure 5), where the power demand was low. In contrast in the offline approach, the battery system only participated at 13 h and with a low value. Notice that the participation of the battery system is crucial for the reduction of cost included in Table 4.

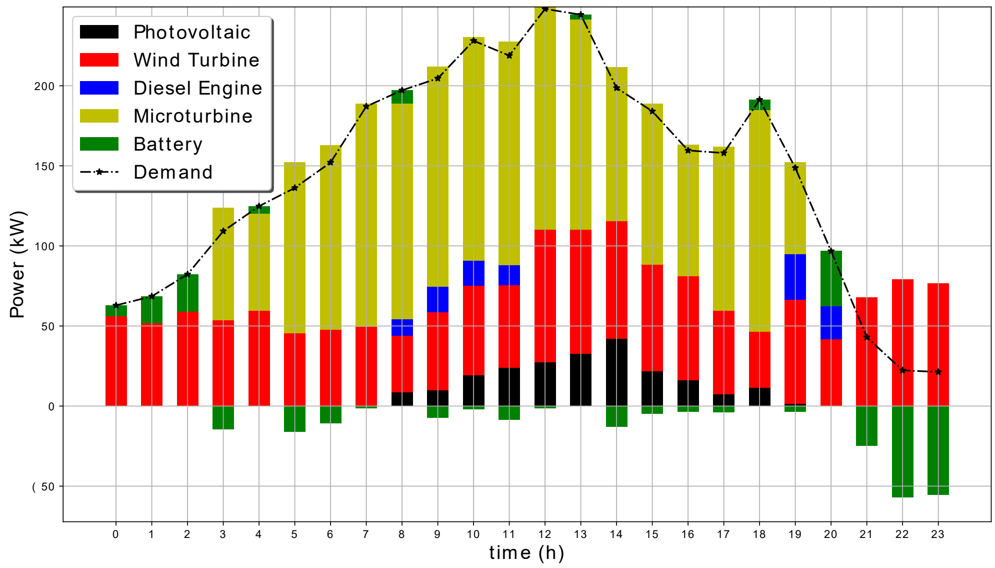

Figure 6. Optimal power scheduling for the time period considered by using offline optimization without taking into consideration uncertainties [38].

7. Conclusions and Further Work

This paper presented a novel strategy to tackle the real-time operation of a micro-grid. In this approach, a model predictive control strategy was used to optimally manage the state and generation of a set of generators in a microgrid. The main conclusions are:

1. Due to the complexity of the problem and the non-linearities, a genetic algorithm was found as a good method to compute the optimal set points for the generation;
2. It was shown that the use of a real-time MPC strategy improved the management of the microgrid studied when uncertainties were taken into consideration in comparison with off-line schedule strategies;
3. The solution obtained optimized the problem while also guaranteeing the reliability of the solution;
4. The genetic algorithm took very little time to solve the problem, which proved its potential use for these types of problems. In addition, it is possible to reduce the time between samples even below five seconds.

As future work lines the following are proposed:

- Analyze the optimal sizing of the energy storage system taken into consideration economical factors and its lifespan;
- Study the problem when a non-islanded microgrid is taken into consideration and the price of the electricity supplied by the main grid changes with time;
- Validate the proposed solution experimentally in a real test-bench.

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