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Dynamic optimal management of a hybrid microgrid based on weather forecasts

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Abstract: Hybrid microgrids containing both renewable and conventional power sources are becoming increasingly attractive for a variety of reasons. However, intermittency of renewable power production and uncertainty in future load prediction increase risks of electric grid instability and, by consequence, restrict the portion of renewable power production in microgrids. In order, to prefigure the upcoming renewable power production, particularly, wind power and photovoltaic power, we suggest using weather forecasts. In addition to illustrating short term renewable power prediction based on ensemble weather forecasts, this paper focuses on optimizing the management of distributed power generation, power storage, and power exchange with the commercial electric grid. Establishing an optimal operating plan for the grid makes the integration of the predicted renewable production more efficient. The optimization problem is formulated as an integer linear program. The operating plan is initially optimized over the upcoming day and then regularly updated and incremented to cover a longer time horizon. After analyzing the obtained plans, we test and evaluate them relative to the observed weather conditions. Finally, we investigate some practical problems that had arisen and we apply a time cascade optimization technique to mitigate the effects of initial conditions and end-of-horizon effects, as well as to take advantage of updated forecasts.

Key words: Economic scheduling, hybrid microgrid management, linear optimization, rolling horizon, near future renewable power prediction, weather forecast

1. Introduction

The intermittency of renewable energy sources limits its power generation contribution in microgrids. As a remedy, several technical solutions were proposed such as flexible alternating current transmission system (FACTS)[1] and modular multilevel converters (MMCs)[2, 3]. For instance, power blackouts are more frequent and risks of grid instability are severer when the percentage of renewable generation increase [4]. Forecasting the future renewable generation could be fundamental to ensure the most economic power generation plan and to lessen relevant risks. Hence, insolation and wind forecasts could be converted to potential photovoltaic and wind power generation, respectively.

A variety of optimization techniques like dynamic programming, meta-heuristics and artificial intelligence, were used to optimize the power management of hybrid grid [5]. In general, power operation problems are strongly nonlinear. Thus, meta-heuristic and population-based algorithms [6] could be trapped in local optima and solution quality is very dependent on parameters' choice. Moreover, hybrid microgrids generally incorporate renewable sources that are intermittent. Nonetheless, several studies like [7, 8] were conducted based on a

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single plan of renewable power generation and therefore it did not account for uncertainty in renewable power generation. In this study, we tried to linearize a fully constrained formulation of power management problem and thus to guarantee the reach of the global optimal solution while keeping the problem formulation descriptive and more realistic. To account for the intermittency in renewable productions, we considered multiple scenarios of weather forecasts for short-term renewable power prediction[9]. Besides, unlike other research works in this field, the optimal management plan obtained from our study is provided as direct operation commands for the grid manager. This study investigates the modeling and the optimization of a detailed microgrid operation plan that takes into considerations various technical constraints. The proposed day-ahead operation scheduling deals with optimal generation plan, optimal power storage plan, and optimal power exchange plan with commercial grid. Weather forecasts are used as inputs to the optimization models after being converted to power production forecasts as it was proposed in [10].

Hence, the research paper [10] was one of the first to propose an integer linear problem formulation to determine an optimal day-ahead management plan for a microgrid, given an ensemble weather forecast. Moreover, the paper has shown the feasibility of the approach and it presented some preliminary results. However, it has briefly described some relevant issues that emerged from the study of the obtained optimal plans such as end-of-horizon effects and the influence of initial conditions, without suggesting solutions to mitigate them. Moreover, Bouaicha et al. [10] has tangentially presented the testing technique of the obtained optimal plans. In this study, we intend to introduce a detailed optimization problem formulation of the power management problem with further analysis of the results. Furthermore, we have minutiously discussed the schedule testing technique. Besides, we investigated the efficiency of rolling horizon optimization (also known as time cascades optimization) as an approach to mitigate end-of-horizon effects and the influence of initial conditions in addition to allowing the use of updated weather forecast.

The modeling of the hybrid microgrid is described in Section 2. The mathematical formulation of the optimization problem is presented and discussed in Section 3. In Section 4, we analyze the optimal plans that results from solving the optimization problem. In Section 5, we provide a method that could be used to test the resulting optimal plans, and in Section 6 we illustrate the use of time cascades optimization to provide additional robustness and to update operating plans in response to new weather forecasts. A summary of the main findings from this study concludes the paper. Besides, we suggest some topics for further investigation in future work.

2. Description of the hybrid microgrid

In this study, we considered an electric microgrid that comprises three distributed fuel based generators, photovoltaic panels, and wind turbines. Given that the cost of energy storage has recently declined to economically attractive levels [11], this study investigates the integration of energy storage units (ESUs) in the microgrid. The contribution of ESUs to reduce the total operation cost has been evaluated. Besides the integration or not of ESUs, in this paper, we studied two different microgrid configurations by allowing or not power exchange with the commercial grid; the resulting configurations are referred in this paper by “isolated” and “grid connected” configurations. A single line diagram of the microgrid is given in Figure 1.

2.1. Wind turbines

In this work, we considered two types of wind turbines in two sites. Technical characteristics of wind turbines are summarized in the annexed Table 1. The problem of maximum power tracking and proper connection of the

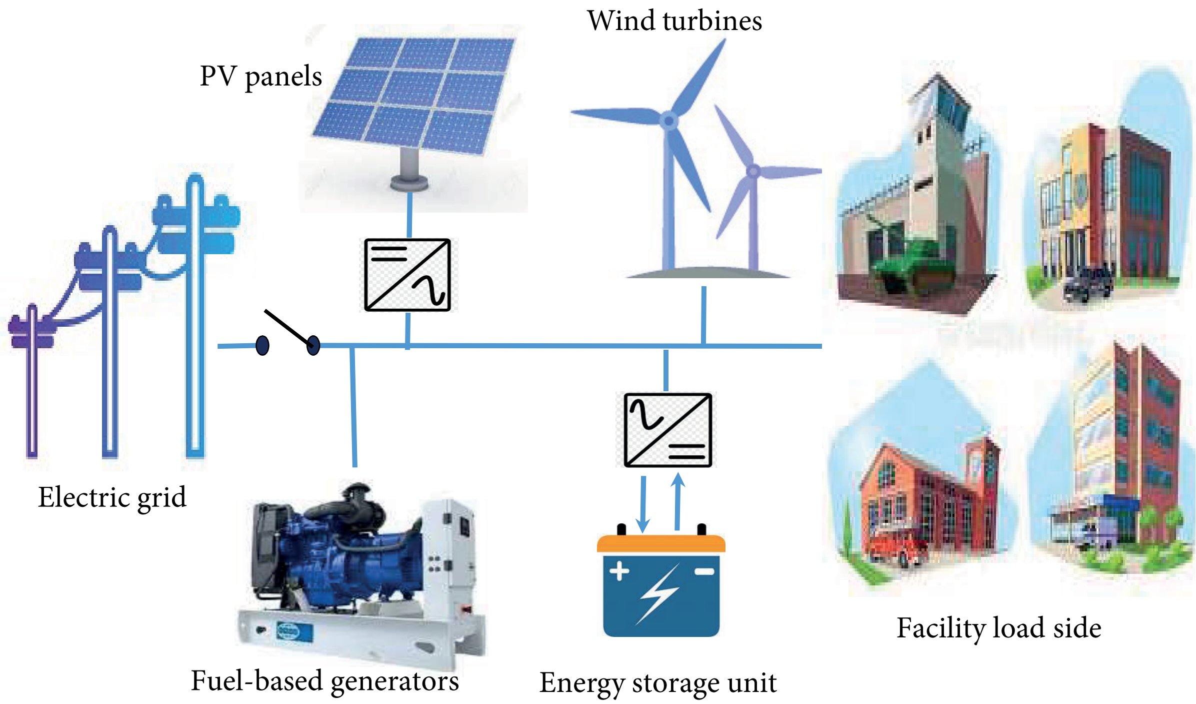

Figure 1. Single line diagram of the studied microgrid.

turbines to the grid were not considered in this approach. The mathematical model of the wind turbine power generation $WindP$ in kilowatts (kW) is given by(1) as a function of the cut-in wind speed V_{ci}, the cut-out wind speed V_{co}, the nominal wind speed V_n and the nominal power P_n [12].

$$WindP(V) = \begin{cases} 0, V < V_{ci} \\ \frac{P_n}{(V_n^3 - V_{ci}^3)} V^3 - \frac{V_{ci}^3}{(V_n^3 - V_{ci}^3)} P_n, V_{ci} < V < V_n \\ P_n, V_n < V < V_{co} \\ 0, V > V_{co} \end{cases} \tag{1}$$

2.2. Photovoltaic panels

Photovoltaic panels have been incorporated in the studied microgrid due to their continuously decreasing production cost and their enhanced efficiency. In fact, recent technologies in the PV cell design, such as multi-junction solar cells, allowed better exploitation of the solar spectrum than single gap solar cells. The limiting efficiency reached the 51.5% level through full spectrum utilization [13]. In [14], the PV power $SolarPower$ generated over a predefined time interval, was expressed as a function of the standard benchmark insolation amount, $Insolation_{standard}$; the observed insolation, $Insolation$; the PV capacity Y_{PV} ; and the derating factor, f_{PV} as:

$$SolarPower = f_{PV} Y_{PV} \left(\frac{Insolation}{Insolation_{standard}} \right). \tag{2}$$

In our PV model, similarly to [15], we considered that the PV power output depends only on $Insolation$, cells' total efficiency $solarEfficiency$, and the panel's area $PanelSurface$ as expressed in in (3). In this study, forecasted PV power generation is calculated based on notional insolation forecasts.

$$SolarPower = solarEfficiency.PanelSurface.Insolation \tag{3}$$

2.3. Fuel based generators

Distributed fuel based generators are usually used for baseload power generation in isolated microgrid. Moreover, it can be used as backup generators for critical facilities in case of disruption of the regular grid power. Given that in this study, we seek to minimize the total operation plan, the optimal plan will tend to operate the most fuel efficient generators. Therefore, we need to compute the fuel consumption in each power production level. The fuel consumption function of a generator is an exponential function [16] which could be approximated by a second order polynomial function after applying a polynomial fitting method that is widely adopted in power management problems [17]. Therefore, to generate power P_g, the fuel consumption function $f_g(P_g)$ is expressed as in (4) [18]:

$$f_g(P_g) \approx a_2 {P_g}^2 + a_1 P_g + a_0, \tag{4}$$

where the fuel consumption coefficients a_0, a_1 and a_2 depend on the generator's characteristics and they could be evaluated experimentally by applying regression model to the observed fuel consumption data. In this study, we approximated the fuel consumption function with a first degree polynomial function as justified in [19].

After being turned on, a generator requires a warm-up period in which the generator is fueled without really generating any power to the grid. Setting a warm-up period in the generator's model reflects the generator's starting cost and it accounts for the time needed for the generated power to be stabilized and ready to be coupled with the grid. Besides warm-up requirement, we set limits in power change for each generator, known as the ramp-up and ramp-down rate limits as detailed in Section 4. In this study, three different generators were considered; their technical specifications (warm up time, fuel consumption coefficients, power production limits,...) were described in the annexed summary Table 1.

Table 1. Technical characteristics of main microgrid components.

Generators				Wind turbine #			Battery	
	Gen1	Gen2	Gen3		1,2,..,5	6,7,..,10		
Prod costs($/kWh)	0.1	0.12	0.14	Vci(m/s)	3	4	Max charge/discharge rate	300/200
Min power (kW)	490	360	250	Vn(m/s)	12	15	Max capacity (Kw)	300
Max power (kW)	640	640	360	Vco(m/s)	15	18	Loss factor	0.2
Warm up (hr)	1	0.5	0.5	Pn(kW)	86	270	Cost ($/kWh)	0.002

Generally, low cost fuel–based generators are used to provide the base load in a standalone hybrid microgrid despite their long warmup time. However, gas generators having relatively higher cost and shorter warm-up time represent backup sources to compensate the small variations of the load. Within the generator power production range, the power output is proportional to the rotation speed. Higher rotation speeds produce more electric current, at the cost of higher fuel consumption. Besides, given that the relationship between fuel consumed and power produced is approximately quadratic, as demonstrated in (4), the rotation speed raised to the power two (squared rotation speed) is used as a decision variable in the proposed linear model. This method, unlike others focusing simply on On /Off status of the generators, gives the grid manager direct commands representing the targeted optimal functioning of generators.

2.4. Energy storage unit

The efficiency of an ESU depicts the fraction of energy that could be withdrawn from the total energy stored. Moreover, an ESU is also characterized by its minimum and maximum charging and discharging rates and by its maximum storage capacity. The efficiency of the modeled ESU represents the round trip efficiency $(1-\alpha)$. Therefore, the state of charge is as expressed in (5) where B_0 is the initial charge, $(1-\alpha)$ is the round trip efficiency, P_{charge} and $P_{discharge}$ are respectively, charging and discharging power. ESU's technical specifications are summarized in the annexed Table 1.

$$B_t = B_0 + \sum_{t' \leq t} ((1-\alpha) P_{charge_{t'}} - P_{discharge_{t'}}). \tag{5}$$

2.5. Weather forecasts

Near future forecasting of renewable power production is a recent research field that could help mitigate the intermittency aspect of renewable energy sources. In our study, potential power productions from wind turbines and PV panels are deduced from wind speed and insolation forecasts. Wind predictions used in this study are related to two different sites (A and B) and they are generated by the weather research and forecast (WRF) model. Hence, WRF is a widely -used regional model for weather forecasts and climate predictions [20]. Wind forecasts are provided by The Naval Research Laboratory in Monterey and by the Naval Postgraduate School (Meteorology Department). Figure 1 illustrates ensemble forecasts of wind speed over 24 hours and relative to a particular site from the two we studied. Each single ensemble member is a forecasted wind speed scenario and it is represented by a separate curve. Ten scenarios were considered that we denoted S1,..., S10. As represented in Figure 2, at the beginning of the forecast time interval, wind speed predictions from various scenarios are very similar but differences increases with time.

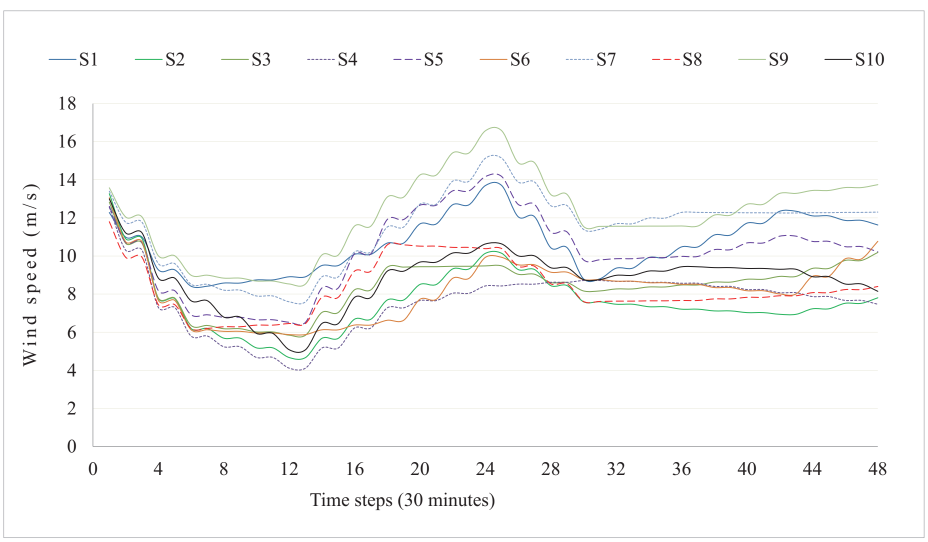

Figure 2. Set of wind speed prediction scenarios on site location B.

Unlike wind speed forecasts, insolation forecasts are not standard output of weather models. Therefore, prediction of insolation is an ambitious process that requires clouds formation prediction based on temperature and humidity data. Hence, the insolation forecasts incorporated in our study are just notional.

2.6. Electric load

In the last decade, several models of short-term load forecasting were proposed. These models use new technics such as artificial neural networks, multilinear regression, fuzzy systems, and hybrid models [21, 22]. This study does not focus on load forecasting. However, we conducted an exploratory analysis of a five year electric power consumption data of a military base. It is worthy to mention that the load presents a consistent behavior slightly changing from one month to another. Within a whole week, load profile is significantly different between the weekend and weekdays. Figure 3 illustrates the variation of the daily load during a month.

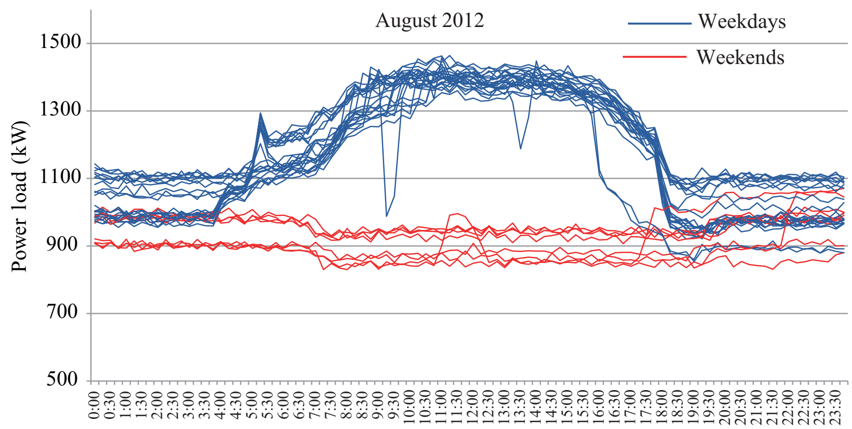

Figure 3. Daily electric load at a military facility in the United States

3. Optimization problem formulation

The main objective of this study is to provide the most economic plan to manage the controllable components of the studied microgrid. Regular economic dispatch problems aim to minimize the generator's fuel consumption or the operating plan of the whole grid [14]. It involves the determination of the optimal power contribution of each generating unit under system constraints either at a specific time, the case of classic economic dispatch, or over a predefined period of time, known as dynamic economic dispatch problem. Our problem formulation represents an improved and a detailed linear formulation of a dynamic economic dispatch problems. The main improvement resides in the fact that the model will help the grid manager not only to optimally control the generating units but also to optimally manage the charge and discharge of the ESU and to manage the power exchange with the commercial grid. Regarding system constraints, the problem formulation takes into account multiple technical and operational constraints such as warm up period, ramp up/ramp down limit and power generation range of generating units. Charging and discharging limits and power exchange rates were also defined in addition to the constraints regulating the power exchange with commercial grid.

The flowchart presented in Figure 4 depicts the whole proposed process that an energy management center can follow in order to optimally manage a hybrid electric grid. The process starts with the load forecasting phase. Given that our study does not focus on load forecasting, we simply consider the real load observed at the studied military facility as the forecasted load. Then, in the following phase, weather forecasts are used to estimate the potential renewable power generation using the mathematic model of both PV panels and wind turbines as discussed earlier in Section 2. The potential renewable power production, in addition to the load forecast, represent the main inputs to the optimization model. This optimization model also requires other inputs such as initial states of the grid components and other external information like electricity market prices. The decision variables that are optimized to obtain the minimum operating cost are the operating plan of each generator, the charge and discharge plan of the ESU, and ,when it is permitted, the power exchange plan with the commercial grid. The optimization process was conducted over a twenty-four hour time interval. Within this planing horizon, the model was discretized into thirty-minute duration time steps. Therefore, during a given time step, we assume that the status of all system components will remain unchanged . The suggested optimization process is depicted in Figure 4. The model formulation is inspired from what was discussed in [10, 18].

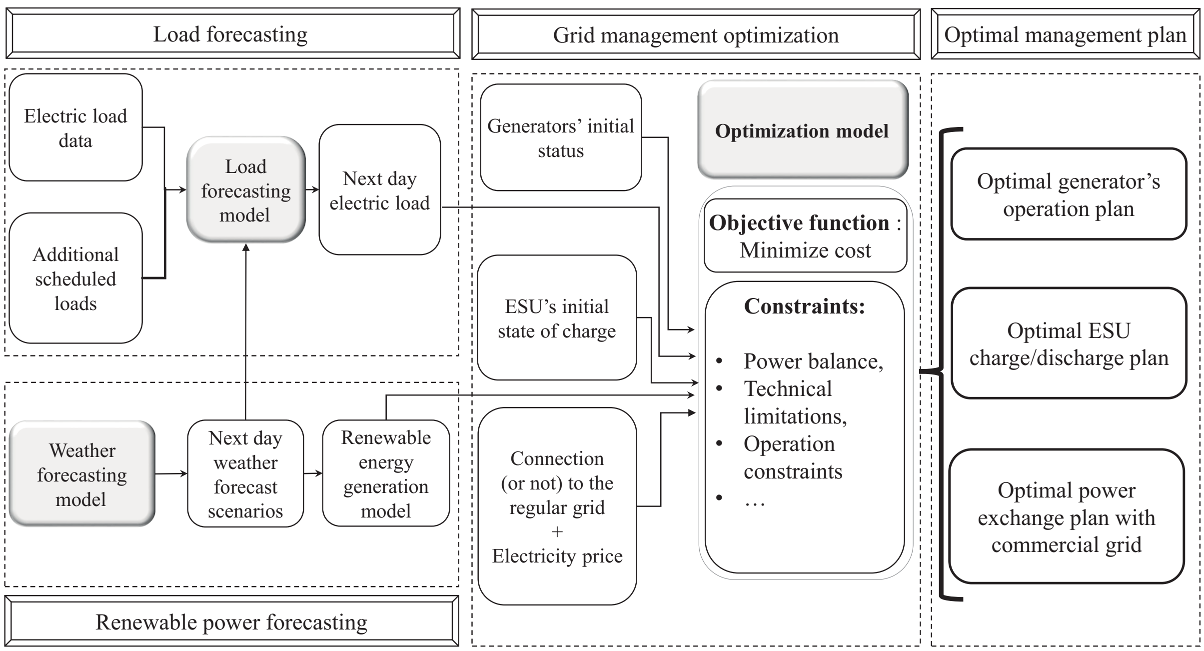

Figure 4. Flowchart of the proposed process for optimal grid management scheduling.

3.1. Nomenclature

3.1.1. Scalars and parameters

ΔT: Time step duration [hours]

$N_{\max}$: Threshold limiting excessive changes in the generator's power output during the optimization time horizon.

$ProdCoef_g$: Power generation coefficient relative to generator g [kW/RPM2],

$ProdCost_g$: Generation cost coefficient relative to generator g [\$/kWh],

$InitialRPM2_g$: Squared speed of generator g at the initial step [RPM2],

$InitialContrib_g$: Initial contribution status of generator g [binary],

$MaxRPM2_g$ (resp. $MinRPM2_g$): Maximum (resp. minimum) squared running speed of the generator g [RPM2],

$warmup_g$: Warm up time required by the generator g [#Time steps],

$Demand_k$: Power load at time step k [kW],
$WindP_{w,k,s}$: Power generation from a wind turbine w given scenario s of wind predictions [kW],
$PurchaseCost_k$ (resp. $SellingPrice_k$): Unit price of purchasing commercial electric power (resp. unit price of selling power to the grid) [$/kWh],
$SolarPower_{k,s}$: Potential PV power generation given a scenario s of insolation predictions [kW],
$MaxCharge_b$ (resp. $MinCharge_b$): Maximum (resp. minimum) power flow of charging battery b [kW],
$MaxDischarge_b$: Maximum power flow of discharging battery b [kW],
$MaxCapacity_b$: Maximum storage capacity of battery b [kWh],
α_b: Ratio of power loss during the charge of battery b,
$InitialStorage_b$: Initial state of charge of battery b [kWh],
$StorageCost_b$: Power storage cost of battery b [$/kWh].

3.1.2. Decisions variables

$ON_{g,k}$: Running status of generator g at time interval k (1 if the generator is running and 0 otherwise),
$RPM2_{g,k}$: Squared rotation speed at time interval k [RPM2],
$CONTRIB_{g,k}$: Contribution or No of generator g at time interval k (1 if contributing and 0 otherwise),
$PCONTRIB_{g,k}$: Contributed Power from generator g at time interval k [kW],
$PBUY_k$ (resp. $PSELL_k$): Power purchased from (resp. sold to) the commercial grid at time interval k [kW],
$PCHARGE_{b,k,s}$ (resp. $PDCHARGE_{b,k,s}$): Rate of charging (discharging) battery b at time interval k given scenario s [kW],
$CHARGE_{b,k,s}$ (resp. $DCHARGE_{b,k,s}$): Binary; charging (resp. discharging) status of batteyr b at time interval k given a scenario s,
$CHANGE_{g,k}$: Binary variable that capture change in generator g running speed at time interval k.

3.2. Objective function

In this optimization problem, we seek to minimize the total cost of operating the studied microgrid during the upcoming 24 hour time window. The total operating cost is calculated in (6) and it includes three terms: the cost of fuel consumed by the distributed generators (first term), the total purchase cost of purchasing power from the commercial grid (second term), and the total expected cost of energy storage where the expectation is taken with respect to the weather scenarios s (third term). Besides, after summing up these three terms, we subtracted the income from vending electric power to the commercial grid (fourth term):

$$Min\,Z = \begin{bmatrix} \sum_{k,g} ProdCost_g ProdCoef_g RPM2_{g,k} \Delta T \\ + \sum_{k} PurchaseCost_k PBUY_k \Delta T \\ + \frac{1}{|S|} \sum_{k,b,s} StorageCost_b PCHARGE_{b,k,s} \Delta T \\ - \sum_{k} SellingPrice_k PSELL_k \Delta T \end{bmatrix} \tag{6}$$

3.3. Constraints

The constraints are deployed to model electric and operation laws regulating the power management and to express grid components' characteristics. In one side, adding many constraints can help making the model more realistic and representative of real problem; but, in the other side, it will make the optimization problem more complex. One of the specificities of this study resides in the integration of many constraints in our model which could be seen as a fully constrained dynamic economic dispatch problem. Nonetheless, the presented model is kept linear by considering linear constraints and by the linearization of nonlinear equations. Hence, the resulting model would be very detailed but still easy to solve with no issue of local optimality.

- The power balance constraint is expressed in Equation (7). It is used to make sure that the total power supply should satisfy the total load at all time steps and for the considered weather scenario s.

$$\left[\begin{array}{l}\sum_{g} PCONTRIB_{g,k} + SolarPower_{k,s} \\ +\sum_{w} WindP_{w,k,s} + PBUY_k + \sum_{b} PDCHARGE_{b,k,s}\end{array}\right] \geq \left[PSELL_k + Demand_k + \sum_{b} \frac{PCHARGE_{b,k,s}}{1-\alpha_b}\right] \quad \forall k \in K, s \in S \tag{7}$$

- Power contribution: The power effectively contributed to the microgrid by a generator g at a given time interval k could be defined as:

$$PCONTRIB_{g,k} = ProdCoef_g \times RPM2_{g,k} \times CONTRIB_{g,k}; \forall g \in G, k \in K \tag{8}$$

In Equation (8) we multiply two decision variables which are: $RPM2_{g,k}$ and $CONTRIB_{g,k}$. Therefore, it is nonlinear. We linearized it using (9), (10), and (11).

$$PCONTRIB_{g,k} \leq MaxRPM2_g \times ProdCoef_g \times CONTRIB_{g,k}; \forall k \in K, g \in G \tag{9}$$

$$PCONTRIB_{g,k} \geq \left[\begin{array}{l} ProdCoef_g RPM2_{g,k} \\ -(1-CONTRIB_{g,k}) MaxRPM2_g ProdCoef_g \end{array}\right]; \forall k \in K, g \in G \tag{10}$$

$$PCONTRIB_{g,k} \leq ProdCoef_g . RPM2_{g,k}; \forall k \in K, g \in G \tag{11}$$

- Warm up time: Equations (12) and (13) impose that a particular generator g could be contributing power only if it was running uncoupled for at least its predefined warm up period or it was initially contributing and it remains contributing since then.

$$CONTRIB_{g,k} \leq ON_{g,k'}; \forall g, k, k'/k - warmup_g \leq k' \leq k \tag{12}$$

$$CONTRIB_{g,k} \leq InitialContrib_g; \forall g, k/k \leq Warmup_g \tag{13}$$

- Battery state of charge: Equation (14) allows to track of the state of charge of the ESU at every time step k, and ensure that it does not exceed its maximum storage capacity. While Equation (15) guarantees the non-negativity of the stored energy.

$$\sum_{k' \leq k} (PCHARGE_{b,k',s} - PDCHARGE_{b,k',s}) \Delta T + InitialStorage_b \leq MaxCapacity_b; \forall b \in B, s \in S, k \in K \tag{14}$$

$$\sum_{k' \leq k} (PCHARGE_{b,k',s} - PDCHARGE_{b,k',s}) \Delta T + InitialStorage_b \geq 0; \forall b \in B, s \in S, k \in K \tag{15}$$

- Battery charging and discharging rates: Equations (16) and (17) apply an upper and a lower threshold on the charging and discharging rate of the ESU.

$$MinCharge_b CHARGE_{b,k,s} \leq PCHARGE_{b,k,s} \leq MaxCharge_b CHARGE_{b,k,s}; \forall b \in B, k \in K, s \in S \quad (16)$$

$$PDCHARGE_{b,k,s} \leq MaxDischarge_b DCHARGE_{b,k,s}; \forall b \in B, k \in K, s \in S \quad (17)$$

- Battery charge and discharge status: To avoid illogical behavior in possible multi-solution optimization problem, we have eliminated the case where an ESU could be charging and discharging simultaneously, by adding Equation (18).

$$CHARGE_{b,k,s} + DCHARGE_{b,k,s} \leq 1; \forall b \in B, k \in K, s \in S \quad (18)$$

- Control the number of variations in power production: For any generator g, Equations (19) and (20) track the number of changes in the generated power (rotation speed) between two successive time steps k and $k-1$. While, Equation (21) limits the total number of changes at most $Nmax$. This constraint is added to eliminate excessive maneuvers in the generator's operation.

$$CHANGE_{g,k} \geq \frac{1}{MaxRPM2_g}[RMP2_{g,k} - RMP2_{g,k-1}]; \forall g \in G, k \in K \quad (19)$$

$$CHANGE_{g,k} \geq \frac{1}{MaxRPM2_g}[RMP2_{g,k-1} - RMP2_{g,k}]; \forall g \in G, k \in K \quad (20)$$

$$\sum_k CHANGE_{g,k} \leq Nmax; \forall g \in G \quad (21)$$

- Equation (22) is deployed to set an upper and a lower thresholds on the generator's running speed $RPM2_{g,k}$.

$$MinRPM2_g ON_{g,k} \leq RPM2_{g,k} \leq MaxRPM2_g ON_{g,k} \forall g \in G, k \in K \quad (22)$$

4. Analysis of results

The model is implemented using the modeling and optimization software: general algebraic modeling system (GAMS) then it is solved using CPLEX 12.2.0.2. The formulated optimization problem includes about 5,300 decision variables and 4,800 constraints. Typical solve times ranged from 5 to 60 s. At the beginning, and to economically evaluate the contribution of the renewable sources, we optimized the operating plan of the microgrid when it includes distributed generators only. Therefore, this initial analysis could be seen as a resolution of a dynamic economic dispatch problem with a fully constrained model. Under these circumstances, the daily power load was satisfied with a total cost of \$3,069.46. Integration of batteries in our system has resulted in a slight decrease of the total cost (\$3,056.94). These costs could be considered as upper bounds for the studied grid operation cost. In this section, we will discuss subsequently the optimal power management plans obtained from the optimization of our model over one single set of weather forecast (scenario) and then over multiple weather scenarios. In each study, we investigated the contribution of ESU and the connection to the regular grid.

4.1. Optimization over a single scenario of weather forecasts

In this subsection, we will not take into account the uncertainty in weather prediction; therefore we will determinedly assume that a single weather scenario will take place. In practice, optimizing over a single forecast scenario is a risky decision. For instance, if the selected scenario overestimate the renewable power generation, the operating plan will fail to meet the demand; conversely, when we predict less renewable power generation than what we really have, we will have extra power production. The modeled microgrid is optimized in various configurations: isolated and grid connected configuration, with and without ESU. When optimizing the model of the isolated power grid without ESU over the forecast scenario S1, the minimum total operating cost is $1,810 and the composition of the resulting power generation plan is as depicted in Figure 5a. Therefore, under the assumptions made, the integration of the renewable sources: wind and solar power, allowed to reduce the operating cost by 41%. Moreover, by adding an ESU in the isolated configuration, the total operating cost was decreased by about 9% . The resulting optimal power generation plan is composed as depicted in Figure 5b. Besides the decrease in the operating cost, when the ESU was included, the backup gas generator Gen3 was not deployed throughout the whole optimization time interval. Small shortfalls in the load are now compensated by discharging the battery rather than by turning on Gen3 as in the previous case. It is worthy to note that in similar cases, an "end-of-horizon" effect might appear. Therefore, the solver focuses only on the optimization time interval and does not have any incentive to keep any stored power in the ESU. In practice, it might be profitable to not use up all the stored energy by the end of the studied time window and keep some energy for the future use. We investigate this issue in Section 6 and we suggest an approach to mitigate it.

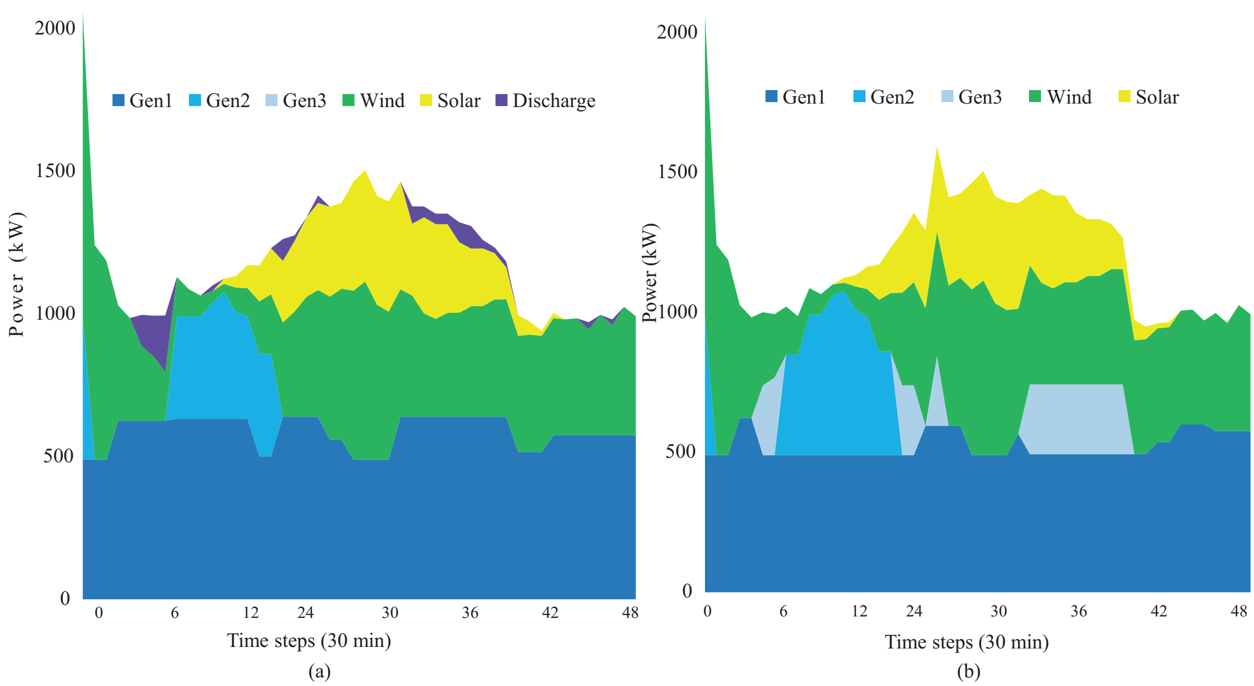

Figure 5. Optimal power generation schedule of the isolated microgrid without ESU (a) and with ESU (b) when optimized over scenario S1 of weather forecasts.

If we allow power exchange between the studied microgrid and the commercial grid, which is referred here as grid connected configuration, the contribution of the ESU becomes less significant and small shortages in the load are now compensated by the common contribution of Gen2, the commercial grid and the discharge of the ESU. After optimizing the grid-connected microgrid with ESU when assuming that scenario forecast S1 has taken place, the optimal power generation schedule and the optimal composition of total load are as presented in Figure 6.

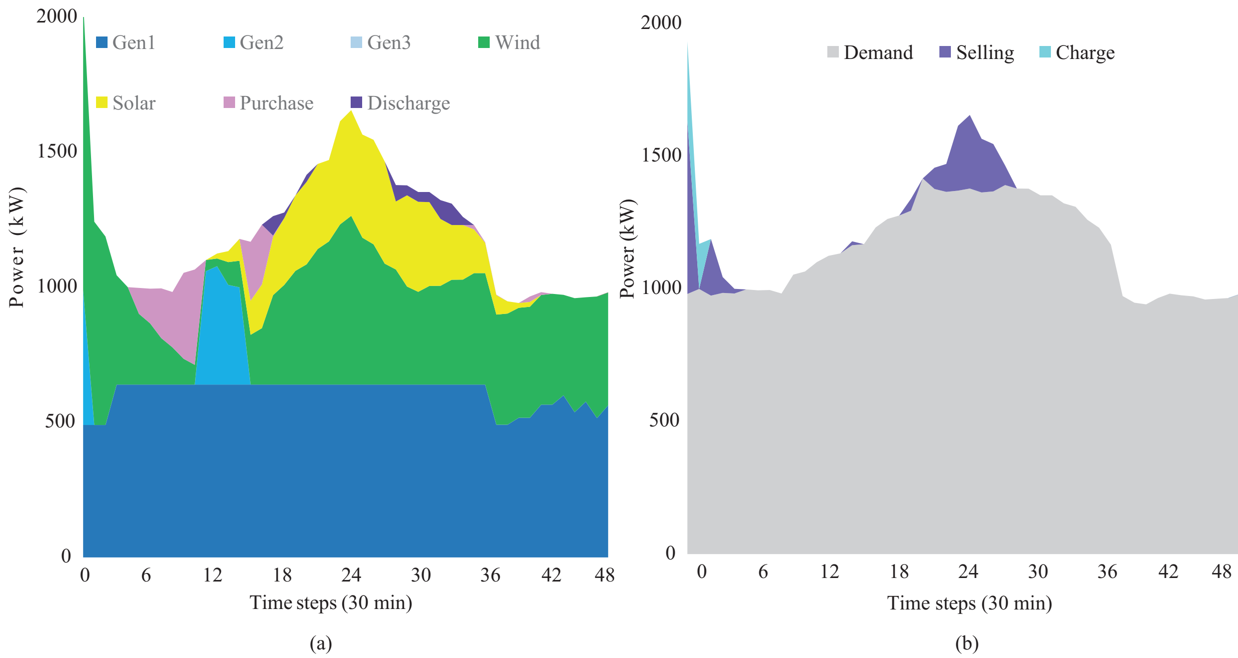

Figure 6. Optimal power generation schedule (a) and Optimal power load (b) of the grid-connected microgrid with ESU when optimized over the scenario S1 of weather forecasts.

4.2. Optimization over multiple scenarios

In any forecast-based model, uncertainty is intrinsic and indispensable for the decision process. As summarized in Figure 7, the total operation cost and the power generation plan of the optimized operating plan vary significantly as a function of the weather forecast scenario. Therefore, the robustness and the quality of the obtained optimal plan, and by consequence the electric power balance of the grid, could be significantly affected by the uncertainties in weather forecasts. To account for uncertainty in weather prediction and to reduce relevant risks, we opted for optimizing the studied model simultaneously over multiple scenarios. By proceeding so, the optimal plan that we get will be able to satisfy all system constraints for any weather scenario from the set we optimized over. Optimizing the model over multiple scenarios simultaneously requires adding more constraints which will never improve the optimal solution but, in opposite, it might make operating cost higher. However, given that the result will not be conditioned by a particular scenario that should take place, the resulting optimal plan will be more robust. In this part, we optimized the system with both isolated and grid-connected configuration over: each scenario separately, all scenarios, the average of all weather scenarios, and the average of the forecasted renewable power productions from all scenarios. The summary of the resulting minimum operating costs for the isolated and the grid-connected microgrid when optimizing over multiple scenarios are illustrated in Figure 7. As it can be seen in Figure 7, when the microgrid is in grid connected configuration, the contribution of the ESU is less significant unlike in the isolated configuration. The 20% loss factor during storage in addition to the 2 cent/kWh storage cost makes storage of power generated from the distributed generators less profitable when the connection to the commercial grid is possible.

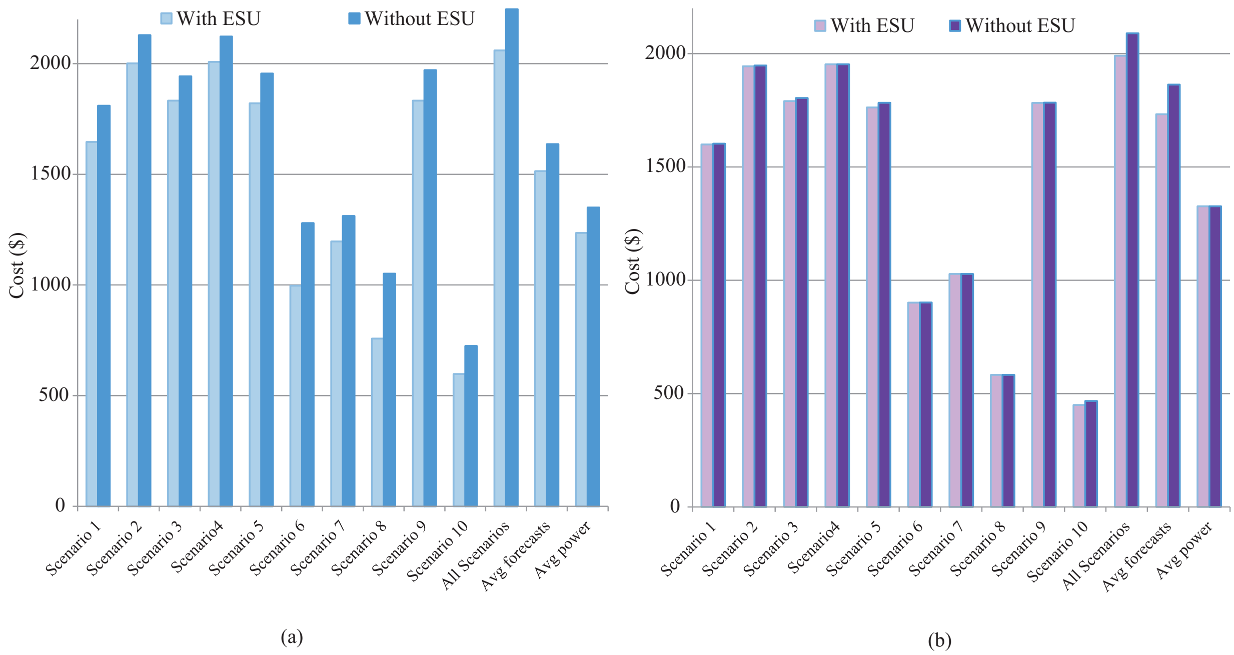

Figure 7. Optimal Costs summary when optimizing the microgrid over multiple scenarios in both isolated (a) and Grid connected configuration (b).

5. Optimal plan testing

In this section, we present a method for evaluating the optimal operating plan provided by the optimization model. This approach can also help the grid manager gain insights about which weather scenario or set of scenarios should perhaps be weighted more heavily in the following optimization time horizon. The first step in evaluating the obtained optimal operating plan consists of observing the real weather parameters seen at the site of interest (wind farm and PV field) and during the studied time interval. Secondly, these observed weather parameters will be used to figure out the power really generated by the renewable sources. Then, we added the real renewable production to the fuel based power generation issued from the execution of the previously determined optimal plan. Lastly, we conduct a comparative analysis between the total power supply previously computed and the power load.

For the application of this testing approach, we assumed that weather scenario S1 took place, which mean that it represents the real observed weather parameters. Then, we tested the two optimal operating schedules obtained after optimizing the model of the isolated microgrid over the average of weather predictions and over the average of renewable power generations from all ten scenarios. Test results are presented in Figure 8.

As it is shown in Figure 8, in one side, the plan obtained from the optimization over the average of weather forecasts had successfully met the demand during the entire optimization time interval. However, we notice that there is an important excess of power production that results in extra dispenses which could be tolerated if the power balance stability between power generation and the load in the studied grid is crucial. In the other side, the plan obtained after optimizing the model over the average of renewable power generations

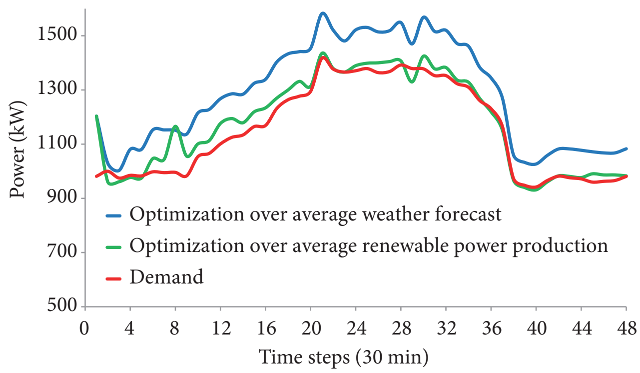

Figure 8. Test of power generation schedules when optimizing the isolated microgrid over the average of weather scenarios and over the average of renewable power productions, given that Scenario S1 takes place.

can meet, very closely, the power demand in the majority, but not all, of the optimization time interval without having significant excess of power production.

6. Illustration of rolling horizon

In this section, we describe a rolling horizon approach that can be used to mitigate end-of-horizon effects and initial condition effects and to take advantage of newly forecasted weather conditions. This approach is also known as a "time cascade."

6.1. Utility of time cascade optimization

Ideally, it is easier and more profitable for an energy management center to get the most economic an operating plan and which covers a longer time interval rather than a limited one. However, the uncertainties in weather forecasts increase over time. Furthermore, most optimization models are susceptible to end-of-horizon effects in which optimal plans use up all stored energy within the planning horizon and do not take into account the following time window. Moreover, the initial conditions such as battery's state of charge and the running conditions of fuel-based generators can influence the optimal operating plans. For example, in the optimal operating shown in Figure 5 and Figure 6, generator Gen2 that was initially running will be turned off just at the beginning of the optimization time interval. For these reasons, we opted for solving the problem with the rolling horizon method. This method requires solving the problem over a short time window and translate forward this time interval so that it covers additional future time at each new solve. The advance in time windows is chosen such that successive optimization time windows overlaps over each other and thus is intended to eliminate end-of-horizon effects. Before each new solve, the electric grid status at the beginning of each time window is updated and thus according to the optimal plan suggested by the previous solve. The process of optimization with rolling horizon is depicted in Figure 9. We considered time windows with 24 h (48 time steps) of length and advance steps of 12 h.

6.2. Optimal operating plans with time cascade optimization

In this part, we applied time cascade optimization technique when solving the optimal scheduling problem and thus to see how the optimal plan could change and to prove how the end of horizon effects have been reduced. As illustrated in Figure 10, we conducted three successive solves based on three different sets of weather forecasts

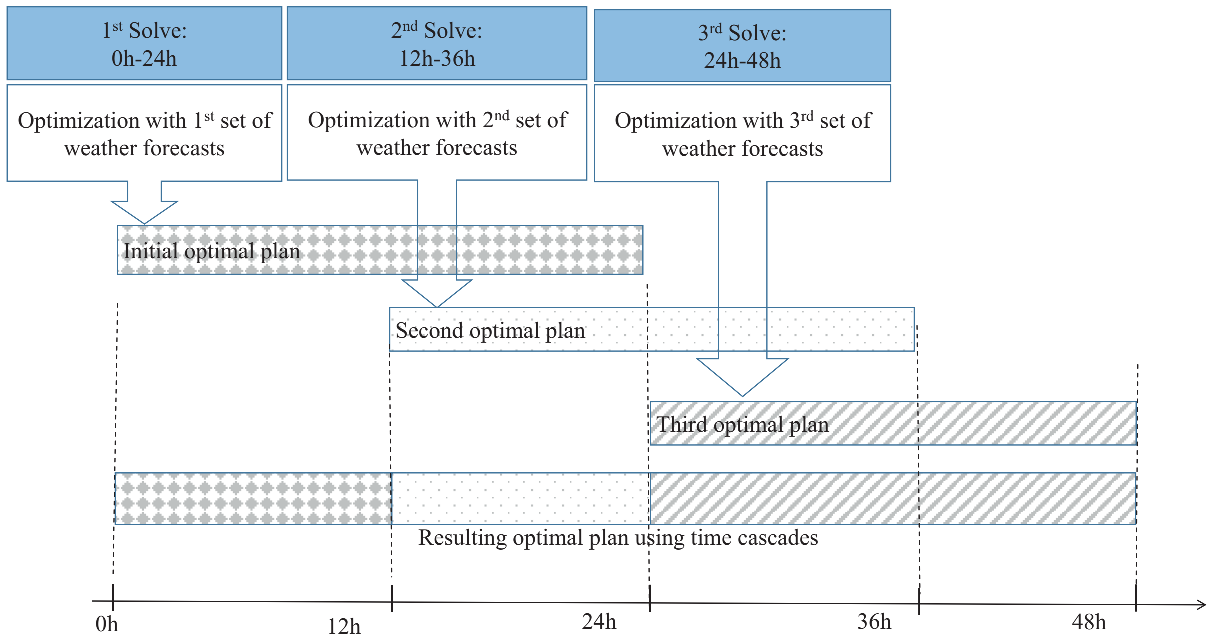

Figure 9. Schematic representation of optimization with time cascades.

with overlapping coverage. Each set covers 24 h period starting, respectively, at midnight, at noon and midnight of the next day. We are particularly interested in studying how the optimal schedule for the second half of the day changes when we use time cascades with the updated weather forecasts, as well as the implications of this change on the overall cost of the solution. When optimizing over the initial set of forecasts only, we obtain an operating cost of \$2,308 and an operating schedule that uses only the diesel generator Gen1 and the gas generator Gen2. However, when we consider the first set of updated forecasts, the operating cost of the same time period becomes \$2,195 . The operating schedule changes as well; in some time intervals, the smaller gas generator Gen3 is used in lieu of Gen2. The optimal plan does not change considerably after including the second set of updates. After further investigation, we found that the wind speed predicted by both sets of updates is very low so that there will be no wind power production and by consequence there will be less uncertainty in the power generation plan.

7. Conclusion

The paper introduced a complete grid management process with an optimized scheduling model that uses an ensemble weather forecast as input. Our computational experiments indicate that using weather scenarios issued from different weather forecasting models leads to significant variation in the optimal operating plans and in total operation costs, underlying the influence of uncertainty in weather forecasting. Besides, we found that including ESU could have great economic impact on the isolated microgrid management. However, this was not the case for grid-connected systems. Furthermore, we have described particular issues such as initial conditions' and end-of-horizon effects and how these factors could influence the operating plan. Therefore, We studied the possibility of using a rolling horizon optimization approach to mitigate these effects and to incorporate recent forecast data as it becomes available. For future research, we suggest running the model over a longer time window in order to help make better decisions such as analysis of the optimal ESU sizing and the analysis of

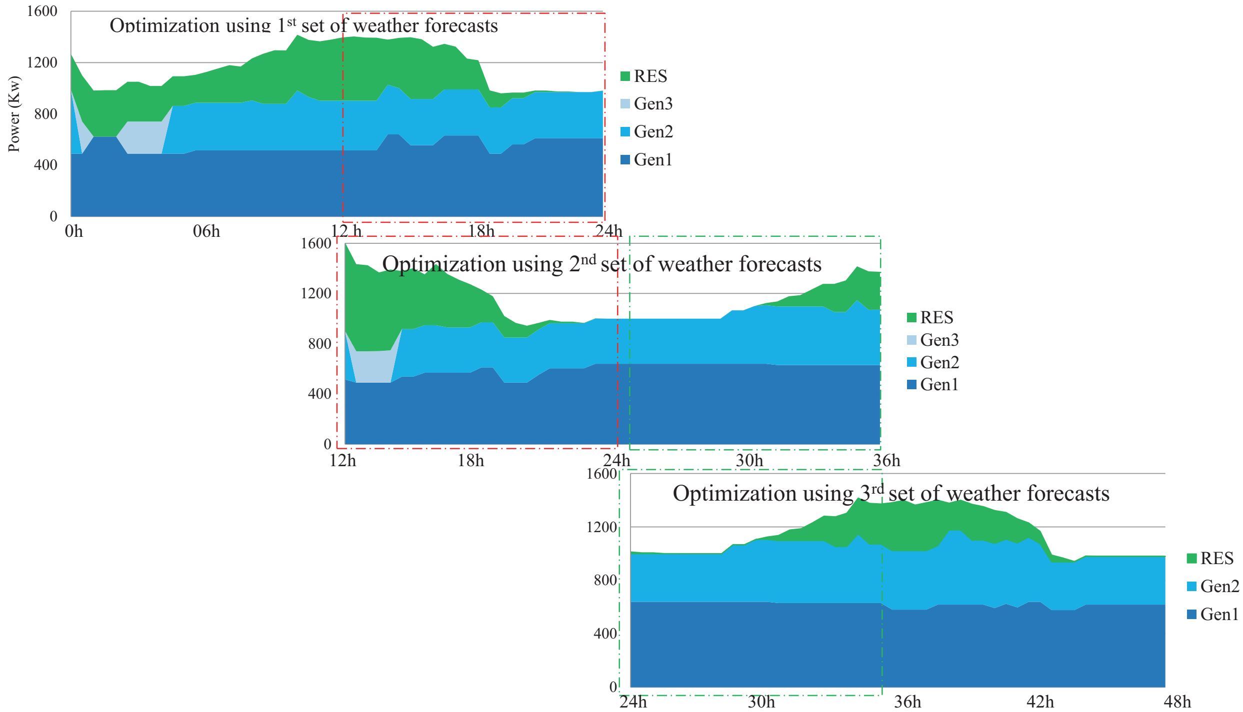

Figure 10. Influence of time cascades optimization in the optimal power generation schedule of the isolated microgrid without ESU.

the performances of some components of microgrid . We also suggest integrating innovative renewable power generation forecasting models such as the multivariate empirical dynamic model discussed in [23]. Additionally, future research may capture the correlation between power load, energy market prices, and weather forecasts.

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