Predictive Dispatch Across Time of Hybrid Isolated Power Systems

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Abstract—The paper proposes a methodology for the optimal dispatch of energy sources in hybrid and isolated energy systems. The proposed approach is based on the formulation and solution of a non-linear discrete optimization problem aimed at optimizing input and output time trajectories for a set of combined generating and storage technologies. Loads and interruptible loads are among controlled variables and are modeled according to their interruption costs. The approach is general enough to be applied to any hybrid system configuration and was developed having in mind complex hybrid system architectures comprising several competing storage technologies (battery, pumping and hydrogen). Test results are aimed at showing the feasibility of the proposed methodology, comparing optimal trajectories to sub-optimal system behavior given by load-following strategies.

Index Terms—hybrid energy systems; storage systems; BESS; discrete optimal control; isolated power systems; microgrids.

I. INTRODUCTION

Isolated power systems are usually built for serving remote communities and areas, whose electrical interconnection with other electric networks is not feasible for geographical, technical, economical or environmental constraints [1-2]. Being installed mostly in remote or scarcely accessible areas, isolated power systems should always maximize the energy sources directly available in loco and minimize the use of external energy resources [3]. This is especially true for poor and secluded communities where capital investments are made through governmental funding [1] and operative costs should be strictly contained.

Maximizing local resources means that, when available, renewable sources such as solar, wind and hydro, have a crucial role in the economy of isolated power systems. This consideration is particularly relevant for all those systems that are built in natural reserves and environmentally protected areas where the impact of polluting emissions should be reduced and the use of conventional fuels should be avoided.

Unfortunately, the intermittent nature of renewable energy sources is cause for severe operating issues. Being permanently disconnected from any other network, isolated power systems cannot exchange power on interconnections. This means that loads are only served by local generation and that energy balance must be strictly respected at any time. Shortage of power can be avoided only by oversizing all equipments, option clearly not economically feasible because it implies huge renewable energy losses [3], or installing conventional fuel-fired generation units (diesel generators, microturbines, etc.) and energy storage systems [2].

Renewable energy sources (RES), back-up generators, energy storage and loads can be grouped in what has been defined a hybrid system [4]. A hybrid system might adopt several competing technologies and different energy carriers depending on available sources and logistical and technical constraints. In isolated systems, where a certain redundancy is to be expected for adequacy and availability issues, hybrid systems can be constituted by several equipments and be characterized by complex architectures.

The coordinated optimization of all hybrid system components is an issue widely recognized in the literature [5], affecting both short term operating [2, 6-14] and long term planning [1, 3-4, 15-16] problems. Many algorithms and methodologies have been presented in literature for the solution of both abovementioned problems and a good analysis of the state of the art is given in [5]. Usually, robust rule-based control schemes [2, 6-9] are adopted exploiting the general knowledge of the system (for example estimating a minimum necessary level of power reserve) or through the adoption of artificial intelligence and fuzzy logic [10-12]. The main drawback of such methods is that they can difficulty deal with a wide variety of possible operating conditions and parameter changes (for example sudden cost increase or shortage of a certain fuel), unexpected unavailability, faults and the presence of several competing technologies. To overcome these issues rule-based approaches are obliged to introduce a relevant number of rules which can result in an excessively complex representation of the system and, consequently, in uncertain and suboptimal behavior.

Several methodologies are aimed at optimizing resources in a specific time framework, usually following a minimum cost or minimum cost/benefit ratio strategy. Some of the approaches proposed in the literature optimizes resources in a short time interval [13] or in real time [14]. In this paper a methodology for a coordinated control of multiple energy sources in an isolated power system is proposed.
The methodology was developed having in mind the experimental hybrid installation under development within the “GE15 Project”. This project aims to design a hybrid PV-wind-diesel-hydrogen-battery-pumping-hydro installation to be employed in remote isolated areas. The system model comprises photovoltaic and wind generators, diesel AC generator, a pumping hydro storage unit, a battery energy storage system (BESS) and an electrolyzer-fuel cell system. The adopted model will also allow to use the hydrogen produced by the electrolyzer for co-combustion in the diesel generator.

The methodology proposed in this paper is based on a discrete-time optimal control problem aimed at minimizing overall operative costs. This choice appears natural in dealing with multiple storage devices whose contribution can be optimized across time on the basis of their capacity, charging and discharging constraints. Test results are presented.

II. HYBRID SYSTEM CONTROL STRATEGY

Optimizing a system composed only by renewable generation and batteries is very simple: batteries are charged if, and only if, generated power is higher than demand, and vice versa. If fueled backup power, or any other form of dispatchable generation, is available, determining an optimal control strategy is not straightforward [5]. This is due to the fact that dispatchable generation makes it possible to charge batteries also when renewable generation does not meet the load and extra production capacity is available at back-up generator. In general, in the presence of multiple storage or fuel options, defining an optimal control strategy for a hybrid system is a challenging task. Several control strategies [6] or operating modes [4] can be defined, together with a set of rules that must be followed in order to select each mode of operation.

If more storage units are added and multi-fuel options are also taken into account, the set of possible choices and operating modes grows to such an extent that simple rules cannot be defined. In particular, in this paper, the system under study will be composed of two renewable sources (wind and photovoltaic generation), three storage facilities (BESS, pumping-hydro station, electrolyzer-fuel cell), and a back-up generator (diesel). Moreover, the possibility of shedding load is considered whenever production cost is higher than load interruption cost. In addition, the possibility of burning hydrogen together with diesel in the back-up generator is taken into account. A single bus scheme [6-7] of this hybrid system is shown in Fig. 1.

As already stated, the presence of multiple storage devices can be suitably treated through optimal control strategy. This is due to the fact that, whenever it must be decided which storage system has to be charged (or discharged) it is necessary to optimize resources across time. Moreover, storage systems might have different response in time, due to their storable capacity and charge/discharge speeds. For such reasons, the proposed approach exploits the forecasts of load and renewable generation over a credible observing time window, as shown in Fig. 2 where the general architecture of the proposed management scheme is shown.

Optimal dispatch of all resources is obtained through the solution of a non-linear optimization problem aimed at minimizing overall cost of production, equipment wear (BESS) and load shedding.

In this study, interruptible loads and interruption costs are modeled, embedding the cost of unmet load into the cost analysis [15]. This means that load curtailment is among the control options available during optimization. Modeling loads according to their interruption costs makes less effective the employment of rule-based operating strategies, since better operating performances could be achieved only through the adoption of predictive approaches (for example, charging storage with fueled power might bring future benefits if forecasted shortages require uninterruptible load to be shed).

The method is general enough to be applied to single operating points or larger time intervals. When applied to a specific operating point (a time interval in which power inputs and outputs are somewhat constant), the solution of the optimization problem mimics a minimum cost load following control strategy since it achieves power balance at the minimum operating cost. This solution will be referred in the following as the “greedy solution” since it aims at minimizing present costs without taking into account the future. In test
results the greedy solution is also adopted as benchmark for testing the discrete optimal control (DOC) solution.

The DOC solution is obtained applying the proposed method to forecasted time varying operating conditions, generating time varying operative set-points (Fig. 2). Compensating deviations from forecasted variables that might impact the power balance is a task of the real-time control layer. The formulation of the control layer logic was considered out of the scope of this paper and could be based on conventional control loop controllers and few overriding rules.

The approach is supposed to be applied recursively, meaning that set-points are recalculated each time a new operating state and new forecasts are available.

Both greedy and DOC approaches employ cost functions based on a database that can be updated at any time during system operation, allowing to take into account fuel price changes, unavailability, and any other disturbing factor that might affect the validity of current operating strategies.

III. DISCRETE OPTIMAL CONTROL ALGORITHM

The discrete optimal control strategy is evaluated through the formulation and the solution of an optimization problem. The problem has been formulated according to the following criteria:

- costs that can be related to the actual dispatch of control resources must be minimized (fuel, operating costs, wear of component, etc.);
- renewable generated power (wind and PV) must always be the maximum possible given weather conditions;
- storage charging must always be allowed if additional generation is available and storage units have not reached maximum level;
- no discriminatory decisions should be taken to favor a particular technology in dispatching;
- uninterruptible (firm) loads should be curtailed only if all (non-firm) interruptible loads have been already shed.

A. Mathematical formulation

The optimization problem is aimed at minimizing operative costs along a selected time window $T$. The objective cost to be minimized is a non-linear function of power inputs and outputs:

$$
\min_p \int_{t=0}^{T} \sum_x c_x(p_x(t)) \, dt
$$

where $x$ refers to the generic power source/demand, $p_x$ is the instant injected or demanded power, and $p$ is the vector of control variables collecting all $p_x$. The non-linearity of functions $c_x$ is due for example to the non-linear dependence of efficiency with respect to power inputs and outputs.

Inputs and outputs are constrained by equality and inequality constraints. A first constraint is given by the load balancing equation which derives from a single bus representation [6-7] of the isolated power system:

$$
\sum_x k_x \cdot p_x(t) = 0 \quad \forall t
$$

where coefficient $k_x$ assumes the value 1 for power sources (generation, storage discharge) and -1 for demand (load, storage charging).

Inequality constraints take into account technical limitations (for example technical minimum power output or maximum rated power, etc.):  

$$
P_{\min} \leq p_x(t) \leq P_{\max} \quad \forall t, \forall x
$$

Storage units require the introduction of state variables referred to the quantity of energy stored. If $s$ denotes the generic storage system, and $q_s$ the energy stored, the following differential equations and constraints must be added to the formulation:

$$
\dot{q}_s = f_s(p(t), q_s(t)) \quad \forall s
$$

with

$$
q_s(0) = Q^0_s
$$

and

$$
q_{\min, s} \leq q_s(t) \leq q_{\max, s} \quad \forall t, \forall s
$$

where $Q^0_s$ is the initial charge and $f_s$ is a generally non-linear function that associates power inputs and outputs to energy stored, taking also into account conversion and standby losses.

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Inputs and outputs are constrained by equality and inequality constraints. A first constraint is given by the load balancing equation which derives from a single bus representation [6-7] of the isolated power system:
This formulation of the problem is characterized by a non-linear expression of the objective function, whereas through simple mathematical manipulations all equality and inequality constraints can be expressed under the linear form \( A \cdot x \leq b \), allowing to solve the problem on multipurpose optimization platforms.

The formulation of equations (6)-(10), depending on the specific technology or energy carrier, is given in the following subsections.

A. RES generating units

Since the approach is aimed at maximizing RES production, the power produced by PV and wind generators, is considered costless. This means that the solution of the optimization problem will have renewable generation always exploited at its maximum availability.

The power inputs from wind generators and from PV, namely \( P_{WG}^i \) and \( P_{PV}^i \), are constrained only by their maximum producibility, as forecasted. It is assumed that whenever RES production exceeds load plus storage charging power, generation can be curtailed or dump loads can be activated. Equation (9) is given by
\[
0 \leq P_{WG}^i \leq P_{WG}^{\text{max}} \quad (11)
\]
\[
0 \leq P_{PV}^i \leq P_{PV}^{\text{max}} \quad (12)
\]

B. Fueled backup generator

In the proposed hybrid system (Fig. 1) this unit is a diesel generator, but clearly the formulation is general enough to be extended to any other fueled generator. The power output of the diesel generator \( P_D \) was limited in (9) considering the existence of technical-economical feasibility limits:
\[
P_D^i = \begin{cases} 
P_D^{\text{max}} & \text{if } P_{D_{\text{min}}} \leq P_D^i \leq P_{D_{\text{max}}} \forall i \\
0 & \text{otherwise} 
\end{cases} \quad (13)
\]

In the solver these constraints are treated by means of relaxation techniques that will avoid the use of integer variables. The technical minimum depends on the specific machine but is usually about 20-30% of the rated power output [3].

Costs are mostly due to fuel consumption and are modeled considering the non-linear dependence of efficiency with respect to electrical power output. Such dependence can be formulated by interpolating efficiency/power output data found in technical sheets. Having fixed the cost of diesel generated thermal energy \( c_{\text{diesel}} \) and expressed efficiency \( \eta_D \) as a function of power output, cost in (7) is calculated as
\[
c_P(P_D^i) = c_{\text{diesel}} \cdot \eta_D(P_D^i) \cdot \Delta t \quad (14)
\]

Further variable costs such as O&M costs can be added. Very often these costs can be extracted by technical sheets, for example if a number of working hours before the first major maintenance intervention is specified. In the case that such pieces of information are not known, general formulations can be adopted.

C. Battery

The quantity of power that is exchanged with the BESS at each time step is described by two variables: \( P_{CB}^i \) and \( P_{DB}^i \) that represent respectively BESS charging and discharging power. Each variable is limited by inequality constraints (9) that take into account, respectively, maximum charge and discharge power.
\[
0 \leq P_{CB}^i \leq P_{CB_{\text{max}}} \quad (15)
\]
\[
0 \leq P_{DB}^i \leq P_{DB_{\text{max}}} \quad (16)
\]

Further inequality constraints are defined in order to limit the State Of Charge (SOC) of the battery. For simplicity it was assumed that roundtrip efficiency is applied to the sole charging phase. This efficiency takes into account losses in the charge/discharge cycle and in the converter, accordingly to the assumption of a single bus model [6]. The problem formulation is general enough to include any other formulation of cycle efficiency.

Under these assumptions equations (6) and (10) are
\[
Q_b^i = Q_b^{\text{max}} + \sum_{l=i}^{t} \left( \eta_{B_{\text{eff}}} \cdot (P_{CB}^l - P_{DB}^l) \right) \Delta t \quad (17)
\]
\[
q_{\text{min},b} \leq Q_b^i \leq q_{\text{max},b} \quad (18)
\]
where \( \eta_{B_{\text{eff}}} \) is the BESS round trip efficiency and \( Q_b^{\text{max}} \) is the initial charge. Please note that, in (17), BESS injected power has been considered twice. As it would be clearer through numerical examples, a suitable choice of storage costs and constraints eliminates the possibility of having both quantities different from zero. In other words, the charging and discharging phases are mutually exclusive. This formulation is mainly due to the need to avoid integer variables and, consequently, skip integer programming.

Knowing the maximum rated BESS capacity \( Q_{B_{\text{max}}} \), the two charging limits in (18) can be derived having fixed a minimum and maximum SOC:
\[
q_{\text{min},b} = \text{SOC}_{\text{min}} \cdot Q_{B_{\text{max}}} \\
q_{\text{max},b} = \text{SOC}_{\text{max}} \cdot Q_{B_{\text{max}}} \quad (19)
\]

The maximum and minimum SOC are inputs of the optimization problem. The maximum SOC is usually 100%, whereas the minimum SOC is chosen according to the maximum acceptable Depth Of Discharge (DOD) in other to maximize the functionality of the battery and keep good level of reserve during real time operation. With respect to this maximum DOD, depending on the battery technology or properties, a life number of cycles \( n_{\text{cycles}} \) can be derived. From these two quantities, it is possible to calculate what is defined battery throughput and represents the expected value of energy that will be cycling through the battery, completing a charge/discharge cycle, before the battery has to be substituted [17]. BESS life throughput can be conservatively evaluated as:
\[
Q_{\text{qmax}} = Q_{B_{\text{max}}} \cdot DOD_{\text{max}} \cdot n_{\text{cycles}} \quad (20)
\]

By formulating BESS throughput it is possible to apply a wear cost to the use of the battery. This wear cost is a variable cost (depending on the actual usage of the battery) and is simply formulated as the ratio between the substitution cost of
batteries and the total throughput.

The most important hypothesis of this model is that the wear cost is associated to the discharge phase only, so that battery charge has no cost and is always maximized. The cost function appearing in (7) is formulated as:

$$c_P = \frac{\text{BESS substitution cost}}{Q_{ph}} \cdot P_{ph} \cdot \Delta t$$  (21)

D. Water pumping storage system

Pumping storage system is formulated very similarly to the BESS. Pumped and generated powers are limited by pump and hydroelectric turbine requirements:

$$0 \leq P_{cw} \leq P_{cw_{max}}$$  (22)

$$0 \leq P_{pp} \leq P_{pp_{max}}$$  (23)

In the pumping system, the maximum SOC can be referred to the maximum level of water storable in the reservoir. Roundtrip efficiency is also introduced, taking into account losses in pump, pipes, and turbine. Constraints in (6) and (10) can be written as:

$$Q_i^p = Q_i^p_o + \sum_{k=1}^{N} \left( \eta_{i,\text{w,r}} \cdot P_{cw} - P_{pp} \right) \cdot \Delta t$$  (24)

$$q_{min} \leq Q_i^p \leq q_{max}$$  (25)

where $\eta_{i,\text{w,r}}$ is the pumping storage round trip efficiency and $Q_i^p_o$ is the initial charge. Minimum and maximum storable energy depend on technical, operative and environmental constraints and can be expressed as function of minimum and maximum volume of storable water and geodetic drop.

As done for BESS, a cost $c_w$, associated to the sole discharging phase and to be included in (7), is formulated. This cost can be estimated considering the average number of working hours before a major maintenance intervention is necessary. This cost is expected to be much lower than wear cost in BESS. With respect to BESS, slower charge/discharge cycles and lower efficiencies are to be expected, depending also on the small-capacity of the equipment under investigation.

E. Electrolyzer/fuel cell

Electrolyzer and fuel cell are modeled considering as control variables their respective power input ($P_i^e$) and output ($P_i^f$), constrained by rated power limits:

$$0 \leq P_i^e \leq P_{e_{max}}$$  (26)

$$0 \leq P_i^f \leq P_{f_{max}}$$  (27)

As proposed in [18-19], if hydrogen is combusted together with diesel in the backup generator, two more control variables, representing respectively the amount of power produced by diesel and the one produced by hydrogen, can be introduced. The exploitation of hydrogen has no cost since it is produced by the electrolyzer; the amount of power produced through hydrogen must not be computed in eqn. (14) evaluating diesel variable costs $c_p$.

Further equality and inequality constraints must be added

$$P_i^e = P_i^{e_{in}} + P_i^{H_e, D}$$  (28)

$$P_i^{H_e, D} \leq r_{H_e, D} \cdot P_i^{e_{in}}$$  (29)

where $P_i^{e_{in}}$ and $P_i^{H_e, D}$ are respectively the power generated in the back-up generator through diesel and hydrogen thermal contribution at step $i$, and $r_{H_e, D}$ is the maximum hydrogen/diesel ratio. If this ratio is kept below a certain limit (about 5-10% [18]), it is reasonable to assume that the efficiency in the diesel generator remains about the same. A substantial increase of efficiency might be reached increasing efficiency in the diesel generator, but this approach is questionable since it might lead to problems due to generation of heavy and harmful combustion knocks [18].

According to this simplifying hypothesis, and having introduced efficiency of both electrolyzer and fuel cell, the quantity of energy stored in the form of hydrogen at the end of time step $i$ can be written as

$$Q_i^e = Q_i^e_0 + \sum_{k=1}^{N} \left( \eta_{e, i} P_i^e - \eta_{f, i} P_i^f - \eta_{D, i} P_i^{H_e, D} \right) \Delta t$$  (30)

and therefore (10) is expressed as

$$q_{min} \leq Q_i^e \leq q_{max}$$  (31)

Operating costs due to components’ wear ($c_e$ and $c_f$) can be added to the formulation, and calculated similarly to what proposed in previous subsections.

F. Loads and interruptible loads

Chronological load curves (i.e. $P_{i}^L$ at each time step $i$) are assumed as inputs of the optimization problem. It is assumed that load is known at each time step and that a certain quantity of such load ($P_{i}^{L_{\text{int}}}$) is characterized by lower interruption costs. The quantity of load to be shed ($P_{i}^L$) is a control variable of the approach and is limited by the total demand. Interruption costs will vary according to the quantity of curtailed load. A simple, but not limiting, hypothesis consists in assuming that interruptible and firm loads have two different constant interruption costs. More complex, non-linear, relationships between the overall amount of load shedding and interruption costs, or time dependent formulation of interruption costs, can be assumed. Clearly more complex formulations are credible only if a fine and detailed knowledge on the nature and distribution of loads is available. The problem formulation is general enough to adopt any interruption cost formulation.

$$0 \leq P_{i}^L \leq P_{i}^L_{\text{int}}$$  (32)

$$c_L = \begin{cases} c_{L_{\text{int}}} & \text{if } 0 \leq P_{i}^{L_{\text{int}}} \leq P_{i}^L_{\text{int}} \\ c_{L_{\text{int}}} & \text{if } P_{i}^{L_{\text{int}}} \leq P_{i}^L \leq P_{i}^L \end{cases}$$  (33)

IV. IMPLEMENTATION AND TEST RESULTS

The problem formulated in (6)-(10), and through all the following equations, has a particularly suitable form since its constraints are linear whereas non-linearities are confined only in the objective function. This feature allows the implementation of the solver into general purpose
optimization platforms. In particular, for test results, a Matlab interior-point routine, that finds minimum of constrained nonlinear multivariable functions, has been adopted.

In the proposed iterative algorithm, the initial guess is chosen as a point internal to the feasibility domain given by the set of inequality constraints. The discontinuity of variable \( P_D \), as formulated in (13), is treated through relaxation, avoiding the formulation of a mixed integer non-linear problem (MINLP).

In particular, starting from a \( P_D \) value close to the maximum diesel power output \( P_{D_{\text{max}}} \), a solution is searched for, considering removed the constraints on \( P_{D_{\text{min}}} \). At a particular time step \( i \), if \( P_D^i \) is lower than \( P_{D_{\text{min}}} \), this variable is constrained to zero and the diesel generator is considered disconnected in the successive iterations.

For the purpose of comparison, a so-called “greedy” algorithm has been introduced. The main feature of this algorithm is that it dispatches resources at a specific time without considering the forecasted demand and RES production. This condition mimics a “load following strategy” [6], since the backup generator produces just what is necessary at that time to balance load. Storage units are charged only when RES production is higher than demand. The same code adopted for DOC has been utilized for generating the “greedy” algorithm, just considering the interval analysis limited to each time step (i.e. \( \Delta t = T \)).

Tests were aimed at showing optimization results for the system represented in Fig. 1 during typical summer and winter operative conditions. RES production and demand were calculated adapting historical time series extracted from the Italian TSO (Terna) database [20].

Demand and production series were scaled considering a 180 kW peak demand and RES generation produced by a 280 kWp photovoltaic plant and an 80 kW wind generator. The system was modeled considering also the presence of a 200 kWh BESS system with a charge/discharge time of 2.5 hours, a 20 kW electrolyzer/fuel cell storage system, a 50 kWh pumping storage unit with a charge/discharge time of 10 hours.

It was assumed a diesel cost of 1 €/liter. Moreover it was hypothesized that the minimum power output is 25% of rated power and that efficiency is 0.6 of maximum efficiency at 25%, 0.9 at 50%, 1.0 at 75% and 1.0 at 100%. Other efficiencies are \( \eta_{\text{BESS}} = 0.8, \eta_{\text{FC}} = 0.5, \eta_{\text{REC}} = 0.7, \eta_{\text{REC}} = 0.5 \).

For the BESS a 30% SOC min and a total number of 2400 cycles before substitution were hypothesized, with a total wear cost of about 0.12 €/kWh. Other substitution costs are negligible with respect to the BESS wear cost. Interruption costs were set at 0.5 €/kWh for interruptible and 2.5 €/kWh for firm loads.

A. Test A: summer day

Figures 3-6 show results of a “greedy” optimization that dispatched resources in each hour without considering future trajectories. This solution is characterized by a good amount of RES power curtailed during the central hours of the day (Fig. 4) and some heavy load curtailments (firm and non-firm loads) at the end of the day. The overall cost for this dispatching solution is 531 €.

This approach cannot deal properly with multiple storage options because it has no vision on how stored energy can be exploited in the future. In Fig. 5, it can be observed how, at hours 10 and 11 when RES production is starting to exceed load demand due to the daily solar peak, the algorithm prefers to charge the BESS, which is rapidly fully charged, instead of the pumping or hydrogen storage units that have been assumed to be characterized by slower charge speed. As a result, at the end of the RES production peak interval, pumping storage is not fully charged even though RES production had been affected by severe curtailments (Fig. 6).

The results of the discrete optimal control approach are shown in Figs. 7-10, where no load curtailments are experienced throughout the day.

In the DOC solution storage units are managed in such way that all storage capabilities are almost fully exploited during the PV peak. Moreover, differently from the previous case, stored energy is not exploited as soon as it is needed (at hour 19) but it is saved for avoiding later load curtailments (see load interruption at the end of the day in Fig 3). Costs are reduced to 339 €. 
B. Test B: winter day

The second case is based on time series referred to the third Wednesday of December. Clearly, since the hybrid system under study depends mostly on solar power, RES production is always not sufficient to satisfy power demand and the back-up generator is needed almost all the time.

The load following greedy solution (Figs. 11-14) is clearly not very satisfying since it implies that storage units are almost never charged. This means that the system is not able to supply enough energy in the last hours of the day when interruptible and firm loads have to be shed causing large interruption costs. The overall cost is evaluated in 933 €.

The greedy solution shows also a somewhat bizarre behavior when at hour 14, hydrogen is produced through the electrolyzer and then sent straight for combustion in the back-up generator (Fig. 11-12). This behavior is due to the fact that demand is only slightly less than RES available power and no stored energy is available to fulfill this gap. The only way to avoid load shedding is to operate the diesel generator at its technical minimum, bringing produced power slightly above demand. The best way of using the resulting power surplus, minimizing cost in the short term, is to produce hydrogen and use it in co-combustion for alleviating fuel costs.
Fig. 11. Case B (winter) load supplied, greedy solution

Fig. 12. Case B (winter) generation dispatch, greedy solution

Fig. 13. Case B (winter) storage dispatch, greedy solution

Fig. 14. Case B (winter) stored energy, greedy solution

Clearly, this anomalous behavior is not shown in the DOC solution (Figs. 15-18) where the back-up generator is always dispatched well above the load following target, allowing full charge of BESS. This solution can be compared to the “SOC_setpoint” strategy, where the fueled generator is operated at full power until the target SOC is reached, or to “full power” strategy where the fueled generator works at its rated power whenever dispatched [6]. The optimal dispatch of the diesel generator in the DOC solution allows to store throughout the day energy enough to avoid most of load curtailment, especially for firm loads.
The DOC algorithm permits also to manage efficiently the storage systems. In the daily dispatch BESS charging is preferred even though if it is characterized by highest wear costs. In fact, differently from the previous summer case where storage charging was costless because of large RES power surplus, in this case power surplus must be generated at an extra fuel cost. Pumping and hydrogen storage are penalized since, due to their low roundtrip efficiencies, extra fuel costs cannot be repaid in terms of avoided interruptions.

The DOC solution is also characterized by a cautious use of stored capacity. In fact, non predictive approaches would have stored energy fully exploited as soon as the back-up generator is not able to balance load (i.e. at hour 18) avoiding interruptions at first but not in the next hours when firm loads have to be shed (Fig. 11). The proposed approach is able to manage more parsimoniously stored resources avoiding most expensive interruptions and minimizing overall costs (Figs. 17-18). The overall cost in this case was estimated in 627 €.

C. Time window choice

One of the main drawbacks of the proposed methodology, comparing to other rule-based control algorithms, is that the time requirements for the solution of the optimization problem might be too high. For example, solving the whole problem optimizing all trajectories at every hour, for one week, through an ordinary interior-point optimization algorithm, can take about 12 hours when run on a common PC.

Still, such solution might also be of scarce interest because a week is probably a temporal framework too large to be employed with the proposed models and to be compatible with weather and RES forecasts.

For this reason, it is shown the dependence that the size of the observing time window $T$ has on overall management costs. Clearly, the following results have significance only if applied to hybrid systems similar to the one under study. In fact, the presence of other technologies that can have different dynamics and larger charge/discharge cycle periods might require longer term simulations and different models (for example if hydro is the main source of generation and it can also be stored in large reservoir).

In this case, based on the previously described winter scenario, it was supposed that the optimization algorithm is run every hour. Hourly dispatch is given by the solution of the DOC algorithm that optimizes future system trajectories in a specific time window. In the next hour a new simulation is run shifting the observation time window. This means that, if for example a 6 hours time window is adopted, resources in the first hour (0am – 1am) are dispatched optimizing trajectories from 0am to 6am, in the second hour (1am – 2am) optimizing trajectories from 1am to 7am, and so on.

Table I gives a projection of optimized costs along or a single day and along an entire winter week. It is shown how a time window of 8-12 hours is already large enough to elaborate an optimal strategy that does not differ that much from the limit case. This is in important find because the shorter is the time window the better is the approximation of real data with forecasted ones. Moreover, a shorter time window, allows to achieve rapid convergence or, alternatively, to adopt a finer time grid improving the system representation.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|}
\hline
$T$ & cost (1 day) & cost (1 week) \\
\hline
1h & 933 € & 5826 € \\
3h & 863 € & 5307 € \\
4h & 839 € & 5078 € \\
6h & 767 € & 4621 € \\
8h & 656 € & 4363 € \\
12h & 629 € & 4258 € \\
24h & 627 € & 4201 € \\
168h & - & 4188 € \\
\hline
\end{tabular}
\caption{Costs vs. time window $T$ (winter scenario)}
\end{table}

For example on a common desktop PC (HP Compaq 8000 Elite CMT PC, with Intel Core 2 Quad CPU Q 9650 3.00 GHz and 4.00 GB RAM), the solution of the optimal problem with a 8h time window and one hour time step takes about 1 minutes. The same problem can take about 10 minutes if a 15 minutes time step is adopted.

V. CONCLUSIONS

The authors proposed a methodology for the optimal dispatch of energy sources in a hybrid isolated power systems. The methodology is based on the formulation and solution of a discrete optimal control problem, assuming the existence of load and production forecasts and a real-time control architecture.

The proposed method is able to deal properly with multiple storage systems and is general enough to be applied to any hybrid configuration. This is a good advantage with respect to rule-based models that have to be specifically configured for a definite configuration and that, in order to deal with complex architecture, must be characterized by an enormous set of rules. The proposed approach ensures also the adoption of optimal dispatch strategy instead of sub-optimal solution that can be reached through the adoption simple rules and load following approaches. A comparison of the economical performances of the proposed approach with respect to a greedy dispatch strategy was assessed in test results.

Test results also showed how computational timings are
compatible with a real-time implementation. Timings are clearly function of the complexity of the system, extension of the observed time window and time step. Feasibility with common weather/RES forecast time framework and granularity of information was shown.

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VII. REFERENCES


