Abstract—This paper proposes a control strategy for a Reverse Fuel Cell used to manage a Renewable Energy Community. A two-stage scenario-based Model Predictive Control algorithm is designed to define the best economic strategy to be followed during operation. Renewable energy generation and users’ demand are forecasted by a suitably defined Discrete Markov Chain based method. The control algorithm is able to take into account the uncertainties of forecasts and the nonlinear behaviour of the Reversible Fuel Cell. The performance of proposed approach is tested on a Renewable Energy Community composed by an aggregation of industrial buildings equipped with PV.

Index Terms—Fuel Cells, Hydrogen, Stochastic Model Predictive Control, Renewable Energy Communities.

I. INTRODUCTION

During last years, the wide spread of Renewable Energy Sources (RESs) has led academic and industrial research to investigate methodologies and technologies which allow a better use of renewable generation to supply energy systems.

In literature, different techniques have been studied to manage RES generation and to optimize the functioning. RESs, such as wind and solar, are variable and hard to predict, therefore many stochastic algorithms have been developed to optimally manage the uncertainties in their forecasts.

The integration of Energy Storage Systems (ESSs) is necessary to deal with RES forecasting errors and uncertainties in power demand, and to obtain power system flexibility, namely the ability of the system generators to react to unexpected changes in load or system component performance. Electrochemical ESSs, such as, batteries, have been widely studied and many works on batteries management can be found in literature. A valid and environmental-friendly alternative to batteries are Power to Hydrogen (P2H) systems in which possible generation surplus is transformed into hydrogen by an Electrolyzer (Ely) and stored in a tank. The same hydrogen can be eventually converted back into electrical power by a Fuel Cell (FC) when power demand exceeds power generation. Depending on the technology, the Ely and the FC can be two different devices or a single reversible unit, called as Reverse Fuel Cell (RFC), working in FC or Ely mode alternatively.

RFC dynamic behaviour is more complex than the one of batteries. Its efficiency depends on the working point according to a nonlinear law and the switching between the two modes cannot be executed close to instantaneously as for batteries, but a transition step has to be considered. In this framework, the objective of this study is to develop an optimal control algorithm able to take into account the uncertainties of RES generation and users demand. In order to satisfy this requirement, we provide a detailed local model for RFC operation efficiency and a Discrete Markov Chain (DMC)-based forecast algorithm for both load and renewable production. Moreover, we use a two-stage scenario-based programming approach to deal with nonlinearities and forecast uncertainties. The result is a stochastic Model Predictive Control (MPC) algorithm which optimizes the economic operation of a Renewable Energy Community (REC). The integration of these different approaches and technologies in the REC framework is not so common in previous works, which focused on an effective formulation of control system algorithms, not using a RFC detailed model, or on RFC behaviour without optimizing global operation.

A REC is a legal entity introduced by the European Commission (EC) through the Clean energy for all Europeans package. In particular, the EC issued two directives IEM and RED II aiming at improving the uptake of energy communities, at making easier for citizens to integrate efficiently in the electricity system as active participants, and at strengthening the role of RES self-consumers and REC.

In this paper, we consider as case study a REC composed of a Photovoltaic (PV) power plant, a RFC unit based on Solid-Oxide Cell (SOC) technology to cope with uncertainties in...
the RES generation and power demand, and an aggregation of industrial warehouses operating as consumers. The manager of the REC administrate both RES generation and RFC operation, according to European directives IEM and RED II.

The paper is organized as follows: section II introduces the system model, section III provides the control strategy, the case study is described in section IV, and the conclusions are reported in section V.

II. SYSTEM MODEL

The schematic architecture of the considered system is reported in Figure 1. The REC is composed of a PV power plant and a RFC serving an aggregation of industrial warehouses. According to EU directives, the REC can supply the consumers’ power demand and also export power to the grid. The industrial aggregation absorbs power from the PV plant and a RFC serving an aggregation of industrial warehouses operating as consumers. The manager of the REC can supply the energy self-consumed between the main grid and RED II. According to Italian transposition of European directives IEM and RED II, a REC is paid for the energy self-consumed between the members of the community and for the energy sold to the main grid. Therefore, it results that

\[ 0 \leq P_t^e \leq P_{\text{max}}^e, \]  

where \( P_{\text{max}}^e \) is the maximum power exportable from REC.

B. RFC

The RFC absorbs power \( P_t^f \) to feed a tank with hydrogen as Solid-Oxide Electrolyzer Cell (SOEC) or generates power \( P_t^e \) by consuming stored hydrogen as Solid-Oxide Fuel Cell (SOFC). SOCs usually work at low pressures and high temperatures reducing crack formation probability and allowing high efficiencies. On the other hand a long start-up is required to reach requested operative temperatures with a time range depending on system size. SOEC and SOFC have different nonlinear efficiencies. Furthermore when switching from a mode of functioning to the other, the RFC does not produce nor consume hydrogen, but it demands power to maintain constant its temperature. We indicate with \( \tilde{P}^e \), the power supplied to the RFC when switching from SOFC to SOEC, and with \( \tilde{P}^f \), the power supplied to the RFC, when switching from SOEC to SOFC. Due to slow thermal response, in this application we have decided to set the RFC always on. Equations describing the RFC functioning and hydrogen tank managing are reported below:

\[
P_t^e = P_t^e \delta_t^e - P_t^f \delta_t^f + \tilde{P}^e \delta_t^e + \tilde{P}^f \delta_t^f, \tag{2}
\]

\[
P^f_{\text{min}} \delta_t^f \leq P_t^f \leq P^f_{\text{max}} \delta_t^f, \tag{3}
\]

\[
P^e_{\text{min}} \delta_t^e \leq P_t^e \leq P^e_{\text{max}} \delta_t^e, \tag{4}
\]

\[
\delta_t^e + \delta_t^f + \tilde{\delta}_t^e + \tilde{\delta}_t^f = 1, \tag{5}
\]

\[
H_{t+1} = H_t + \frac{\Delta}{E^{\text{H}}} (\phi_t^e - \phi_t^f), \tag{6}
\]

\[
H_{\text{min}} \leq H_t \leq H_{\text{max}}, \tag{7}
\]

where: \( P_t^e \) is the power exchanged by the RFC, positive when absorbing and negative when generating; \( P^e_{\text{max}}, P^e_{\text{min}}, P^f_{\text{max}} \) and \( P^f_{\text{min}} \) are, in the following order, maximum and minimum power of SOEC and SOFC; \( H_t \) is the Hydrogen Level in the Tank (SoH); \( H_{\text{min}} \) and \( H_{\text{max}} \) are minimum and maximum SoHs; \( E^{\text{H}} \) is the tank capacity, defined according to the transformation 1 MW h = 30 kg; \( \phi_t^e \) and \( \phi_t^f \) are the power exchanged by the RFC with the tank, respectively in SOEC and SOFC mode. \( \delta_t^e \) and \( \delta_t^f \) are nonlinear functions of \( P_t^e \) and \( P_t^f \), respectively.

\[ \delta_t^e, \delta_t^f, \tilde{\delta}_t^e \text{ and } \tilde{\delta}_t^f \] are binary variables representing the operating mode of the RFC, respectively: SOEC mode, SOFC mode, transition to Solid-Oxide Electrolyzer Cell (t-SOEC) mode and transition to Solid-Oxide Fuel Cell (t-SOFC) mode.

In order to switch from SOEC to SOFC, the RFC has to operate in t-SOFC mode before operating in SOFC mode, similarly in order to switch from SOFC to SOEC, the RFC has to operate in t-SOEC mode first. Furthermore, when t-SOFC or in t-SOEC mode occurs, the RFC must operate as a SOFC or as a SOEC, respectively, in the following time interval. Finally in order to curtail mechanical and thermal stress, the number of switches between the operating modes should be limited. All of these conditions are modeled with the following mixed integer constraints:

\[
\delta_t^e + \delta_{t+1}^e \leq 1, \quad \delta_t^f + \delta_{t+1}^f \leq 1, \tag{8}
\]

\[
\delta_t^f + \delta_{t+1}^e \leq 1, \quad \delta_t^e + \delta_{t+1}^f \leq 1, \tag{9}
\]

\[
\tilde{\delta}_t^e - \delta_{t+1}^e \leq 0, \quad \tilde{\delta}_t^f - \delta_{t+1}^f \leq 0, \tag{10}
\]

\[
\sum_{j=0}^{M} (\tilde{\delta}_t^e) \leq a, \quad \sum_{j=0}^{M} (\tilde{\delta}_t^f) \leq a. \tag{11}
\]

Constraint (11) is introduced to limit mechanical and thermal stress; \( a \) is the maximum number of switches allowed in \( M \) time-steps from the current time \( t \).

C. REC

According to Italian transposition of REM and RED II [12], a REC is paid for the energy self-consumed between the members of the community and for the energy sold to
the grid. The self-consumed energy $\Delta \cdot P_{ac}^{en}$ is defined as the minimum between the energy exported by the manager and the one consumed by the members of the REC:
\[
P_{ac}^{en} = \min(P_{e}^{en}, P_{t}^{I})
\] (12)
where $P_{t}^{I}$ is the power demand at time $t$ of the warehouses aggregate.

Since according to the manager economic return (17), introduced below, both $P_{ac}^{en}$ and $P_{t}^{I}$ will be maximized, (14) can be rewritten by the following inequalities:
\[
P_{ac}^{en} \geq 0,
\] (13)
\[
P_{t}^{I} \leq P_{e}^{en},
\] (14)
\[
P_{ac}^{en} \leq P_{t}^{I}.
\] (15)

D. Power Balance, Operational Costs and Available Data

During every quarter hour $t$, the following power balance has to be matched:
\[
P_{res}^{t} = P_{t}^{r} + P_{e}^{t},
\] (16)
and the manager economic return is:
\[
J_{t} = \Delta ((c^{m} + c^{e}) P_{ac}^{en} + c^{e} P_{t}^{I})
\] (17)
where $P_{res}^{t}$ is the power generated by RES; $c^{e}$ is the energy sell-back price; $c^{m}$ is an incentive bestowed by the Italian Ministry of Economic Development (MISE) and $c^{e}$ is the restitution of grid charges since $P_{ac}^{en}$ does not burden on the grid [12]. The objective of the paper is to maximize the REC manager economic return, assuming that at time step $t$, given a time horizon $T$, the following data are available:
- a set of $S$ scenarios each one containing a forecast profile of RES generation $\{P_{res}^{en}(s)\}_{k=0}^{T-1}$, a forecast profile of load $\{P_{t}^{L}(k)\}_{k=0}^{T}$, and an associated confidence probability $\pi_{s}(s)$ associated at the mentioned scenario $s = 1 \ldots S$;
- the current SoH $H_{t}$;
- all energy prices from time $t$ to time $t + T - 1$.

III. Optimal Management

In this section we propose the optimal management algorithm, which decides a control action at each time-step $t$, given the data above reported. At quarter hour $t$, we will indicate with $k = 0,1, \ldots , T-1$ the time sequence $t, t+1, \ldots , t+T-1$.

In the following, we first introduce the method adopted to obtain load and RES forecasts, and then we formulate a Mixed Integer Linear Problem (MILP), finally used by an MPC controller to perform the optimal management.

A. Load and RES Generation Forecasts

In [5], a methodology named Instantaneous Growing Stream Clustering (IGSC) has been proposed to model time series of interest with a DMC through an adaptive online algorithm with minimal computational efforts. The constructed DMC can then be used to sample possible future scenarios (forecasts) given the current actual state of the DMC.

The states dwell in the same space of the measurements (e.g. in the active power-time plane) and are characterized by the mean of the measurements that happened to be closest to that state. For each state also the number of measurements, their variance, and covariance between the variables are kept in memory.

The algorithm presents just one parameter: $\tau$, a positive real number, which regulates how different from current states must be a new measurement in order to add a new state to the DMC (the optimal choice of $\tau$ has been investigated in [13]).

The algorithm is detailed in the following for the case of two variables.

Let $m(x) = [m_{1}(x), m_{2}(x)]$ the mean vector of a state $x$, $\sigma(x) = [\sigma_{1}(x), \sigma_{2}(x)]$ the variances of a state $x$, $\rho(x)$ the covariance of a state $x$ and $N(x)$ the measurement assigned to a state $x$. Let $O_{k} = [O_{1,k}, O_{2,k}]$ be the current observation and $x_{k-1}$ the last timestep state. The steps of the proposed algorithm for each incoming measurement are the following:

1) Matching step: Find the two states closest to $O_{k}$, respectively $F_{k}$ and $S_{k}$;

2) State Adaptation: create a new state with the same coordinates of $O_{k}$, connect it with $F_{k}$ and assign it to $x_{k}$ (current state) if:
- $O_{k}$ is outside the circle of diameter $F_{k}S_{k}$;
- The Euclidean distance between $O_{k}$ and $F_{k}$ is greater than $\tau$;
otherwise do not create a new state, instead let $x_{k} = F_{k}$

3) Weight Adaptation: The state $x_{k}$, to which $O_{k}$ has been assigned, is updated. For each variable $i = 1, 2$, the mean is updated as follows:
\[
m_{i}(x_{k}) := \frac{m(x_{k}) \cdot N(x_{k}) + O_{k}}{N(x_{k}) + 1} (18)
\]
With similar formulas the variance of each variable and the covariance between each pair of variables are updated for current state $x_{k}$:
\[
\sigma_{i}(x_{k}) := \frac{\sigma_{i}(x_{k}) \cdot N(x_{k}) + (O_{k} - m_{i}(x_{k}))^{2}}{N(x_{k}) + 1} (19)
\]
\[
\rho(x_{k}) := \frac{1}{N(x_{k}) + 1} \cdot \rho(x_{k}) \cdot N(x_{k}) + \frac{1}{N(x_{k}) + 1} \cdot (O_{1,k} - m_{1}(x_{k})) \cdot (O_{2,k} - m_{2}(x_{k})) (20)
\]
Finally, $N(x_{k})$ is increased by one.

4) Edge Adaptation: A link between the past state $x_{k-1}$ and the current state $x_{k}$ is created, if it does not exist. Moreover, the weights of all the links starting from the past state are changed to reflect the transition probability.

The resulting DMC is used for the simulation of possible future scenarios, given the current state and using the transition probabilities between the states.

In order to add some variability, the simulated values are not exactly equal to the mean of the states, but they are added to a realization of a bivariate normal random variable having
as covariance matrix the variance and covariances computed for each state during the weight adaptation steps.

To be used by the control algorithm, the DMC is first trained on historical data. Then, at time $t$, given the actual values of RES generation $P_{\text{res}}^t$ and power demand $P^t$, a set of 300 paths of length $T + 1$ is generated. The set is then reduced to 10 scenarios with same length and a probability $\pi_s(s)$ is associated to each of them, applying the scenario reduction method introduced in [14].

**B. Piecewise linearization of nonlinearities**

Equation (5), for any $t = k$, is nonlinear, since $\phi^l_k$ and $\phi^s_k$ are nonlinear functions of $P_{\text{gen}}^t$ and $P^t$, i.e. $\phi^l_k = g^l(P_{\text{gen}}^t)$ and $\phi^s_k = g^s(P_{\text{res}}^t)$. To cope with this, Special Ordered Set of type 2 (SOS2) variables are introduced. SOS2 is an ordered set of non-negative variables, of which at most two of them can be non-zero and if two are non-zero they must be contiguous in the ordered set. Given the set $\Lambda = \{\lambda^j\}_{j=1}^L$ of length $L$ it has to be:

$$
\sum_{i=1}^L \lambda^i = 1, \quad \lambda^i \geq 0
$$

(21)

if $\lambda^{l'} > 0$:

$$
\lambda^{l'} = 0; \quad \lambda^{l'+1} \geq 0 \quad \forall l' \in [1, L - 1]
$$

(22)

SOS2 variables are adopted to approximate functions $g^l(\cdot)$ and $g^s(\cdot)$, as follows:

$$
P^\mu_k = \sum_{i=1}^L \lambda^i_k P^{\mu,i}_k, \quad \phi^\mu_k = \sum_{i=1}^L \lambda^i_k \phi^{\mu,i}_k
$$

(23)

where $\mu = \text{el, f}$, $P^{\mu,i}_k$ are the independent variable breakpoints, $\phi^{\mu,i}_k$ are the value of functions at the breakpoints (intercepts: $\phi^{\mu,i}_k = g^\mu(P^{\mu,i}_k)$), and $\lambda^i_k$ are the SOS2 variables.

**C. Two-stage Stochastic Optimization Problem**

In a two-stage stochastic programming approach the sum of two cost functions is minimized, the first-stage one refers to the actual objective of the optimization, the second-stage one is suitably defined to minimize the expected violation of constraints that involve random variables. Specifically, such uncertain constraints are relaxed by introducing positive auxiliary variables, called recourse variables. The value of these variables is then minimized according to second-stage cost function, that is suitably defined to take into account the probability distributions of the random variables. For details, the reader is referred to [6, 7].

According to (17), first-stage cost function is:

$$
J^f_s = -\sum_{k=0}^{T-1} \Delta \left( c^f + c^e \right) P^\text{ac}_k + \phi^e_k P^e_k
$$

(24)

and constraints are (11)–(14), (15)–(16), (23). Constraints that involve random variables are (15) and (16). Therefore, first we rewrite (15) as equality constraint, $\forall k \in [0, T - 1]$:

$$
P^\text{ac}_k + \gamma_k = P^f_k, \quad \gamma_k \geq 0,
$$

(25)

where $\gamma_k$ are slack positive variables; then, we rewrite (16) and (17), as second-stage constraints: $\forall k \in [0, T - 1]$ and $\forall s \in [1, S]$,

$$
\xi^s_k(s) \geq P^\text{ac}_k + \gamma_k - P^f_k(s),
$$

(26)

$$
\xi^s_k(s) \geq 0,
$$

(27)

$$
\xi^s_k(s) \geq P^f_k(s) - P^\text{ac}_k - \gamma_k,
$$

(28)

$$
\xi^s_k(s) \geq 0,
$$

(29)

$$
\gamma_k \geq 0,
$$

(30)

$$
\chi^s_k(s) \geq P^e_k + P^e_k - P^\text{res}_k(s),
$$

(31)

$$
\chi^s_k(s) \geq 0,
$$

(32)

$$
\chi^s_k(s) \geq P^\text{res}_k(s) - P^e_k,
$$

(33)

$$
\chi^s_k(s) \geq 0.
$$

(34)

where $\chi_k^s(s)$, $\chi_k^e(s)$, $\xi_k^s(s)$ and $\xi_k^e(s)$ are the recourse variables; finally, the second-stage cost function is defined as follows:

$$
J^s_t = \sum_{k=0}^{T-1} \sum_{s=1}^S \pi_t(s) \left[ (\chi^s_k(s) + \xi^s_k(s)) \omega^+ + (\chi^s_k(s) + \xi^s_k(s)) \omega^- \right],
$$

(35)

where $\omega^+$ and $\omega^-$ are penalty weights. In (35) we can observe how, using the probability distribution $\pi_t(s)$ of scenarios, recursive variables are minimized as higher is the probability that the corresponding scenarios occur.

To conclude, the two-stage stochastic optimization problem is formulated by the following MILP:

$$
\min_{\{X_k\}_{k=0}^{T-1}} \left( J^f_s + J^s_t \right)
$$

(36)

subject to: (11)–(14), (15)–(23), (26)–(34).

**D. Control Algorithm**

The algorithm consists in solving (36) at each time-step $t$. Then, the receding horizon is adopted: to apply just the values calculated for the instant $k = 0$ to the controlled variable, move to the successive time-step $t + 1$, and repeat the same procedure. Forecasting errors are compensated outside the optimization problem with the aim of maximizing the income of the REC manager. Therefore, if the actual RES generation is higher than the expected one, $P^e_k$ is increased to exploit the surplus in generation and increase the income; instead, if it is lower, $P^e_k$ is decreased, when possible according to (1)–(7), otherwise $P^e_k$ is decreased. Changes in $P^e_k$ and $P^f_k$ are made to keep always satisfied (16).
IV. CASE STUDY

The considered case study is an aggregation of industrial warehouses equipped with PV generators. The industrial aggregation is supposed to undergo Italian regulation [12]. Data of power demand and PV generation are taken from [15]. In particular, power demand was taken as it was, while PV generation was increased in nominal power with respect to the values reported in [15]. Values of nominal power demand and nominal PV generation are listed in Table I.

To get forecasts, the method described in Section II-A is applied with $\tau = 0.1$. The DMC is trained with historical data in [15]. Figure 2 shows an example of 10 scenarios generated for RES production and power demand at the midnight of the third day of simulation in comparison with their real values.

The developed model correlates the power, in terms of hydrogen production (SOEC) or consumption (SOFC), with the number $N_c$ of SOCs constituting the RFC, the operating temperature $\theta$ of the SOCs, and the electrical powers used $P^\text{el}$ and produced $P^f$. The investigated relations are:

\[
\eta^{\text{el}} = \frac{N^\text{el}_H LHV^c_H}{P^\text{el}_H^{\text{el}}} = \frac{\phi^{\text{el}}}{P^\text{el}}, \quad (37)
\]
\[
\eta^f = \frac{P^f}{N^\text{el}_H LHV^c_H} = \frac{\phi^f}{P^f}, \quad (38)
\]

where $\eta^{\text{el}}$ and $\eta^f$ are efficiencies in SOEC and SOFC mode, $N^\text{el}_H$ and $N^\text{el}_H$ the flow of hydrogen produced in SOEC mode and consumed in SOFC mode, $LHV^c_H$ the Lower Heating Value of hydrogen, $P^{\text{el}}$ the power that has to be given in SOEC mode to produce $N^\text{el}_H$, ensuring isothermic operation, warming up the reagents and compressing the produced hydrogen, finally $P^f$ the electric power produced by the SOFC deducted by the power to warm up the reagents. SOC working conditions are fixed in order to optimise the operation basing on authors’ previous work [16].

In the following equations we provide the numerical expressions of $\eta^{\text{el}}$ and $\eta^f$.

\[
\eta^{\text{el}} = \left\{ \begin{array}{ll}
0.74 & \\
\beta_1 \frac{\phi^{\text{el}}}{N_c} + \beta_2 \frac{P^{\text{el}}}{N_c} + \beta_3 \theta & \frac{\phi^{\text{el}}}{N_c} \leq (\alpha_1 \theta^2 - \alpha_2 \theta + \alpha_3) \\
\alpha_1 \theta^2 - \alpha_2 \theta + \alpha_3 & \frac{\phi^{\text{el}}}{N_c} > (\alpha_1 \theta^2 - \alpha_2 \theta + \alpha_3)
\end{array} \right. \quad (39)
\]

\[
\eta^f = 8.06 \times 10^{-3} \frac{P^f}{N_c} - 8.89 \frac{P^f}{N_c} + 1.85 \times 10^{-2} \theta - 9.29 \times 10^{-1} \left( \frac{P^f}{N_c} \right)^2 - 8.95 \times 10^{-6} \theta^2 - 8.88 \quad (40)
\]

where $\alpha_1 = 4.87 \times 10^{-4}$, $\alpha_2 = 9.46 \times 10^{-2}$, $\alpha_3 = 46.34$, $\beta_1 = 2.32 \times 10^{-4}$, $\beta_2 = 0.33$ and $\beta_3 = 7.7 \times 10^{-4}$. The profiles of the two efficiencies, for the constant operating temperature $\theta = 1123$ K are shown in Figure 3.

From (37)–(39) and (40), it is possible to express functions $\phi^{\text{el}} = \eta^{\text{el}}(P^{\text{el}})$ and $\phi^f = \eta^f(P^f)$, then used by the control algorithm as described in Section II-B.

The number of SOCs composing the RFC was estimated by setting the upper power in SOEC mode equal to the maximum value of power demand. The maximum number of switches between operating modes is set to 3 in 4 h.

V. SIMULATION RESULTS

To test the performance of the proposed control algorithm, one week has been simulated, using the data from the midnight of June 4th to the midnight of June 12th, 2017. The values adopted for $c^e$, $c^{\text{el}}$ and $c^f$ are listed in Table I. $c^e$ is shown in Figure 4 and it represents to the actual energy clearing market price in Italy. Notice that the energy prices considered in this application are the characteristic values at the beginning of 2021, before the sudden rise of natural gas price in Europe.

Table I

| Parameter | Symbol | Value |
|-----------|--------|-------|
| Main Grid Connection Nominal Power | $P^{\text{max}}_N$ | 340 kW |
| Storage Capacity | $E^h$ | 400 kWh |
| RFC Number of SOCs | $N_c$ | 100 |
| Minimum Power in SOEC mode | $P^{\text{min}}_f$ | 7.2 kW |
| Maximum Power in SOEC mode | $P^{\text{max}}_f$ | 160 kW |
| Minimum Power in SOFC mode | $P^{\text{min}}_H$ | 3.5 kW |
| Maximum Power in SOFC mode | $P^{\text{max}}_H$ | 40 kW |
| RFC Power Demand in t-SOEC mode | $P^f$ | 2.6 kW |
| RFC Power Demand in t-SOFC mode | $P^H$ | 1.3 kW |
| Nominal Power Demand | $P^N$ | 163 kW |
| PV Plant Nominal Power | $P^{\text{nom}}_P$ | 150 kW |
| MISE Incentive | $c^m$ | 0.11 €/kWh |
| Restitution of Grid Charges | $c^r$ | 0.009 €/kWh |
The values of penalty weights $\omega^+$ and $\omega^-$ were set to 1, about ten times higher than the values of the other prices. The control algorithm has been implemented in MATLAB, integrated with General Algebraic Modeling System (GAMS) to write the optimization problem, solved by CPLEX solver.

Figures 5–6 show an example of obtainable simulation results. In particular in Figure 6 we can observe how the RFC is managed: during the nights, the algorithm decides to discharge the hydrogen tank and to never switch between two modes since any transition represents an additional load that can not be satisfied in absence of RES generation. Furthermore we can observe that the majority of switches is obtained during the days with less RES generation.

We finally remark that the total earning obtained within the week operations has resulted to be equal to 2044.45 €, against 1955.58 € obtained in the same conditions without the RFC.

In this paper a control strategy for a RFC used to manage a REC is proposed. A two-stage scenario-based MPC algorithm has been designed to decide the best economic strategy to be followed during operations. Such an algorithm uses a suitably defined DMC based method to forecast consumers demand and renewable generation, and a nonlinear model the of RFC efficiency derived from a physical based model at local level. The algorithm has been successfully tested on a REC composed by an aggregation of industrial buildings and a PV plant.

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