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On the Optimal On-Line Management of Photovoltaic-Hydrogen Hybrid Energy Systems

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Abstract

We present an on-line management strategy for photovoltaic-hydrogen (PV-H_2) hybrid energy systems. The strategy follows a receding-horizon principle and exploits solar radiation forecasts and statistics generated through a Gaussian process model. We demonstrate that incorporating forecast information can dramatically improve the reliability and economic performance of these promising energy production devices.

Keywords: receding horizon, stochastic, Gaussian process, solar, hydrogen.

1. Introduction

Hybrid technologies are attractive alternatives for satisfying increasing energy needs in diverse industrial sectors. The main idea is to couple components that generate power from different sources such as fossil fuels or renewables. With this approach, it is possible to overcome cost and efficiency limitations of the individual components and, in turn, minimize the overall system costs. A promising hybrid is the so-called photovoltaic-hydrogen (PV-H_2) system. A schematic representation is given in Figure 1. The idea is to generate electricity from solar radiation to fulfill a given load. The excess power is stored in a battery bank or in the form of hydrogen produced by electrolysis. The stored hydrogen can be converted back to electric power by using a fuel cell system. Power conditioning devices are used to regulate the voltages of the different devices, which are connected to a common busbar.

An important obstacle affecting the reliability of PV-H_2 systems is the fact that the main energy source is intermittent and highly uncertain. To illustrate this, in Figure 2 we present the total solar radiation for year 2004 at location 41° 59' N/87° 54' W in the Chicago, IL area. Another important issue is the fact that the components might have significantly different efficiencies (giving rise to different levels of power losses). Consequently, it might not be immediately evident which component is the optimal one to store and provide energy at a particular time. Motivated by these issues, researchers have devoted significant effort to developing on-line control or management strategies. Most of the strategies reported so far have been based on fuzzy logic and neural networks techniques (Vosen and Keller 1999, Ulleberg 2004). While these strategies might seem practical at a first glance, they are not general enough to handle economics, forecasts, and operational limits systematically. In this work, we present a general on-line management strategy for PV-H_2 hybrid systems. The strategy follows a receding-horizon (RH) technique and incorporates an economic objective function. With this strategy, we can directly study the effect of using forecast information on the overall operating costs. We demonstrate that using management strategies that neglect the future radiation trends can severely affect the system costs and reliability. Motivated by this observation, we derive a strategy to obtain approximate forecasts and associated statistics through a Gaussian process modeling technique. We then use this information to derive a stochastic RH strategy that satisfies the load reliably.

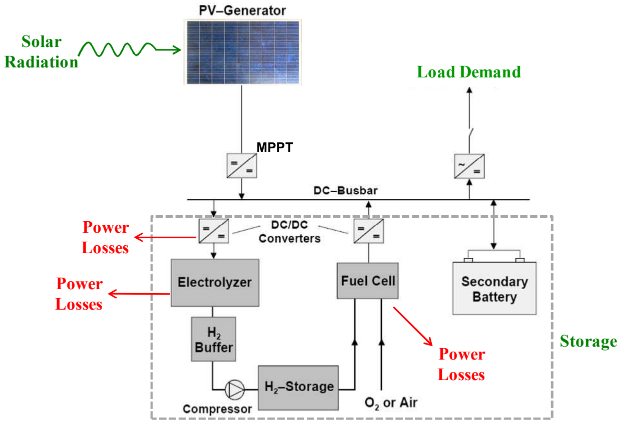

Figure 1. Photovoltaic-Hydrogen Hybrid System

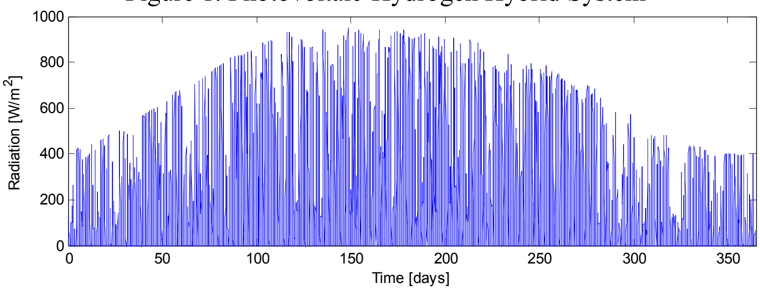

Figure 2. Profile of total solar radiation in Chicago IL, 2004.

2. System Dynamic Model

The dynamic model comprises a systems wide power balance. The power entering through the solar module at time t_k is denoted by P_k^{PV}(kW). This can be calculated by using the measured radiation G_k^T (kW/m^2) and the module design characteristics. The electric current will go through a DC-DC converter that will seek to match the electric current voltage to the voltage of the distribution busbar. This conditioning process has an inherent efficiency θ_{PV} and generates power losses. The remaining power $\theta_{PV}P_k^{PV}$ is sent to the busbar to satisfy the current load P_k^{LOAD}. The excess power can be used to produce hydrogen in the electrolyzer and/or to charge the battery. In order to run the electrolyzer, the power extracted P_k^{EL} passes through a buck DC-DC converter, which brings the current voltage down to the operating voltage of the electrolyzer. The efficiency of this step is θ_{BU}. The remaining power $\theta_{BU}P_k^{EL}$ enters the electrolyzer. The conversion process to hydrogen has an efficiency θ_{EL}. The *net* price for each power unit produced by the electrolyzer is given by C_{EL}. Since hydrogen can be seen as an asset, the net price can be negative. The produced power $\theta_{BU}\theta_{EL}P_k^{EL}$ in the form of hydrogen is stored in a storage system modeled by a difference equation of the form $E_{k+1}^{H2} = E_k^{H2} + \Delta_k\,(\theta_{BU}\theta_{EL}P_k^{EL} - P_k^{FC})$, where E_k^{H2} is the total energy stored (kWh) at time t_k and $\Delta_k = t_{k+1} - t_k$ (hr). The hydrogen *state of charge* is defined as $SOC_k^{H2} =$

$100\frac{E_k^{H2}}{E_{MAX}^{H2}}$, where E_{MAX}^{H2} is the nominal maximum capacity (kWh). A certain amount of power P_k^{FC} can be withdrawn from the storage to feed a fuel cell and generate electric power. The conversion process has an efficiency θ_{FC}. The cost for each unit of power produced by the fuel cell is given by C_{FC}. The remaining power is then passed through a boost DC-DC converter that brings the voltage of the current up to the operating voltage of the busbar. The process has an efficiency θ_{BO}. The remaining power $\theta_{FC}\theta_{BO}P_k^{FC}$ is sent to the distribution busbar. The system might be able to buy a given amount of power P_k^G from the grid in order to balance the system. This power will have a cost C_G which depends on the location and the degree of independence required by the application (e.g., for a stand-alone system, $C_G = \infty$). Excess power at the busbar can also be dumped to the grid or environment, which is modeled by variable P_k^D. The cost of dumped power is C_D . If the power is dumped to the grid, this cost becomes an asset (set by net-metering rates). The power remaining at the busbar can be used to either charge or discharge the battery. The net battery power P_k^B is calculated as $P_k^B = \theta_{PV}P_k^{PV} + P_k^G + \theta_{FC}\theta_{BU}P_k^{FC} - P_k^{EL} - P_k^{LOAD} - P_k^D$. The battery balance is $E_{k+1}^B = E_k^B + \Delta_k P_k^B$, and the state-of-charge is $SOC_k^B = 100\frac{E_k^B}{E_{MAX}^B}$. The fixed model inputs are P_k^{PV} and P_k^{LOAD}. The degrees of freedom are P_k^{EL}, P_k^{FC}, P_k^G, and P_k^D.

3. Management Strategy

The RH strategy solves, at time t_k, a linear programming (LP) problem of the form

$$\min_{P_j^{EL},P_j^{FC},P_j^G,P_j^D} \sum_{j=k}^{k+N-1} C_{EL}P_j^{EL} + C_{FC}P_j^{FC} + C_GP_j^G + C_DP_j^D$$

$$\begin{aligned}
s.t.\ & E_{j+1}^{H2} = E_j^{H2} + \Delta_j\left(\theta_{BU}\theta_{EL}P_j^{EL} - P_j^{FC}\right), \quad j = k,\dots,k+N-1\\
& E_{j+1}^{B} = E_j^{B} + \Delta_j P_j^B, \quad j = k,\dots,k+N-1\\
& E_k^{H2} = given, \quad E_k^B = given\\
& P_j^B = \theta_{PV}P_j^{PV} + P_j^G + \theta_{FC}\theta_{BU}P_j^{FC} - P_j^{EL} - P_j^{LOAD} - P_j^D, \ j = k,\dots,k+N-1\\
& 0 \geq SOC_j^B \leq 100, \ \ 0 \geq SOC_j^{H2} \leq 100, \ \ j = k,\dots,k+N.
\end{aligned}$$

From the solution of the LP, we obtain the optimal future trajectory for the electrolyzer, fuel cell, grid, and dump powers that minimizes the operating costs, maximizes H_2 production and, simultaneously, satisfies the load and the storage limiting levels. To solve the LP, we need information of the future solar power $P_j^{PV}, j = k,\dots,k+N-1$ expected to be available. Important research questions that, to the best of our knowledge, have not been addressed so far are: What is the economic impact of folding forecast information in on-line management strategies? What is an appropriate forecast horizon? How can we get accurate forecast information? To address these questions, we perform a numerical case study. The efficiencies of the components are obtained from Vosen and Keller (1999). The unit costs are obtained from Stoll and von Linde (2000). A constant load of 1kW is assumed. The maximum peak PV power is 5 kW. We first solve an open-loop optimal control problem using *perfect* forecast information for a horizon of 365 days ($N = 365x24 = 8760$ hours). We use the optimal cost as a reference for the *best economic performance possible* over one year of operation. This is on the order of \$1,000/yr. We then run the closed-loop RH strategy spanning the year for different horizons $N = 1, 6, 12, 24, 3x24, 7x24, 14x24$ (hr) with an update time of $\Delta_k = 1$ hr and compute the corresponding relative costs. This required extensive computations. For each scenario, approximately 8,500 LP problems needed to be solved. The 14-day forecast LP contains 2,000 constraints and 1,000 degrees of freedom and can be solved in less than one second with a state-of-the-art solver. The results are summarized in Figure 3. Several interesting and unexpected conclusions can be drawn from this study: (1) the relative operating costs decay exponentially to zero as the horizon is increased; (2) for a purely reactive strategy ($N = 1$ hr), the relative costs can go as high as 300%; and (3) the *overall best cost can be obtained with a finite forecast* ($N = 24x14$ hr). This last result has important practical implications because it is often difficult to obtain accurate long-term weather forecasts. In addition, note that the economic penalty of using a short forecast of 24 hr is just an increase of 10% in relative costs, whereas the penalty for a forecast of 12 hr is 31%. This implies that a practical horizon should be sufficiently long to capture the periodicity of the daily radiation. The reason for these strong economic penalties becomes evident from Figure 4. Here, we present the power profiles for the fuel cell for both the open-loop and the $N = 12$ hr closed-loop cases. Note that *shorter forecasts induce more aggressive control actions,* which in turn affect the costs. As we increase the horizon, the system is allowed to react more *proactively,* which is reflected in smoother controls.

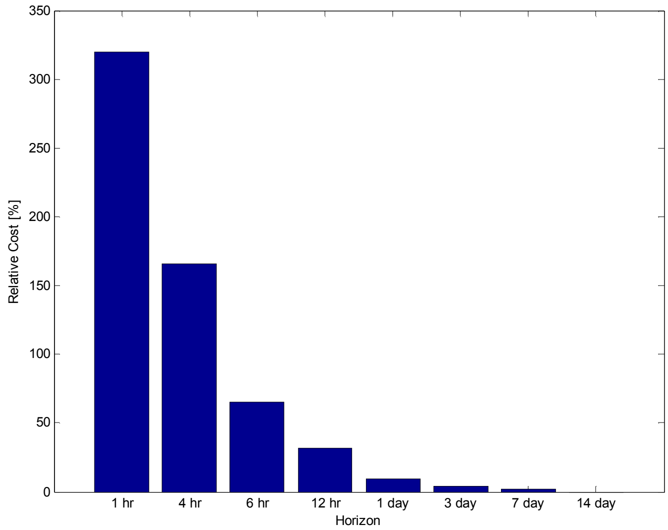

Figure 3. Impact of forecast horizon on economic performance.

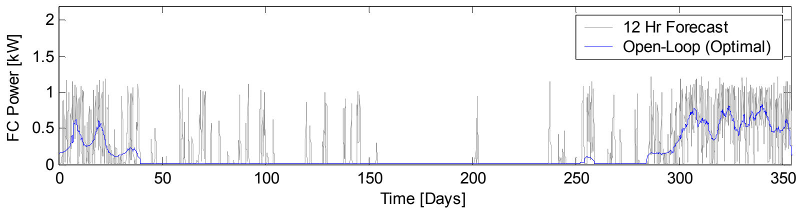

Figure 4. Impact of forecast horizon on power profiles.

4. Gaussian Process Model and Stochastic Management Strategy

Gaining access to solar radiation predictions can be complicated or impractical. In addition, if the forecast is not accurate enough, the management strategy can run out of stored energy prematurely and will be unable to satisfy the load. This situation is particularly critical in stand-alone systems. In the absence of forecasts, we could assume that the radiation profile of the next day will be similar to that of the previous day. Another option is to use historical data to construct a dynamic empirical model. For instance, a time-series approach could be used to build an auto-regressive (AR) model.

An approach that has recently received attention is Gaussian process (GP) modeling (Rasmussen and Williams 2005). The idea is to construct an AR model by specifying the structure of the covariance matrix rather than the structure of the dynamic model itself. We have found that this feature makes the GP modeling particularly flexible. Consequently, this was the approach used in this work. Because of space restrictions, we present only the basics of the GP algorithm. We construct a model by regressing the future radiation (output) y_{k+1} to the current radiation and to the radiation observed T time steps ago (we use $T = 24$ hr to enforce periodicity). We define the inputs $x_k = [y_k, y_{k+1-T}]$ to give $y_{k+1} = f(x_k)$. We collect a number of input-output pairs as training data sets represented by Y and X. We assume that the inputs are correlated through an exponential covariance function

$$K(x, x', \vartheta) = \vartheta_1 \exp\left(-\frac{1}{\vartheta_2}\,\|x - x'\|^2\right) + \vartheta_3,$$

where $\vartheta_1, \vartheta_2, \vartheta_3$, are parameters estimated by maximizing the log likelihood function:

$$\log p(Y|\vartheta) = -\frac{1}{2} Y K^{-1}(X, X, \vartheta) Y - \frac{1}{2} \log\det\big(K(X, X, \vartheta)\big).$$

Once the parameters are obtained, we can compute mean predictions Y^T with associated covariance K^T at a set of test points X^T. In our context, these are the time-varying radiation trends. The predictive equations are

$$\mathrm{Y}^\mathrm{T} = K(X^T, X, \vartheta) K^{-1}(X, X, \vartheta) Y$$

$$\mathrm{K}^\mathrm{T} = K(X^T, X^T, \vartheta) - K(X^T, X, \vartheta) K^{-1}(X, X, \vartheta) K(X, X^T, \vartheta).$$

In Figure 5, we present the mean forecast and 100 samples drawn from the normal distribution $N(Y^T, K^T)$ at a particular day. We use approximately 400 training data sets. Note that the distribution captures the true radiation values, implying that the assumed covariance structure is reasonable. We use the GP forecast distributions to derive a stochastic RH strategy that minimizes the *expected* cost and satisfies the constraints for all possible realizations of the future radiation. The objective function takes the form:

$$\min_{P_j^{EL}, P_j^{FC}, P_j^G, P_j^D} \quad \boldsymbol{E}\left[\sum_{j=k}^{k+N-1} C_{EL}\, P_j^{EL} + C_{FC} P_j^{FC} + C_G P_j^G + C_D P_j^D\right].$$

Symbol $\boldsymbol{E}[.]$ denotes the expectation operator. We solve this infinite-dimensional problem using a sample-average approximation strategy. To test the stochastic strategy, we construct scenarios by sampling the predicted GP distribution. In Figure 6, we compare the performance of the optimal open-loop strategy with perfect forecast (RH optimal) with a strategy that uses the mean forecast (GP mean) and one that uses 100 samples (GP samples). The GP samples LP contains 16,000 constrains and 5,000 degrees of freedom and can be solved in 3 seconds. In addition, we analyze the performance of a simple strategy that propagates the radiation of the last day to the next day (RH simple). In the top graph, we present the state-of-charge of H_2 storage along the year. Note that the GP mean and GP samples approach obtain similar levels to those obtained by RH Optimal. On the other hand, the total H_2 produced with RH Simple is 10% lower. In the bottom graph, note that GP mean fails to satisfy the power demand at one instance during the year (indicated as large or infinite cost). RH simple is the least reliable strategy; failing at 4 instances (overlapping due to time scale). On the other hand, the stochastic GP samples strategy is always able to satisfy the demand.

5. Conclusions

In this work, we have derived a receding-horizon strategy to perform the on-line management of PV-H_2 hybrid energy systems. We conclude that a few days long forecast is sufficient to obtain an acceptable economic performance. In addition, we demonstrate that capturing the uncertainty of the future radiation trends is critical to satisfy the load reliably.

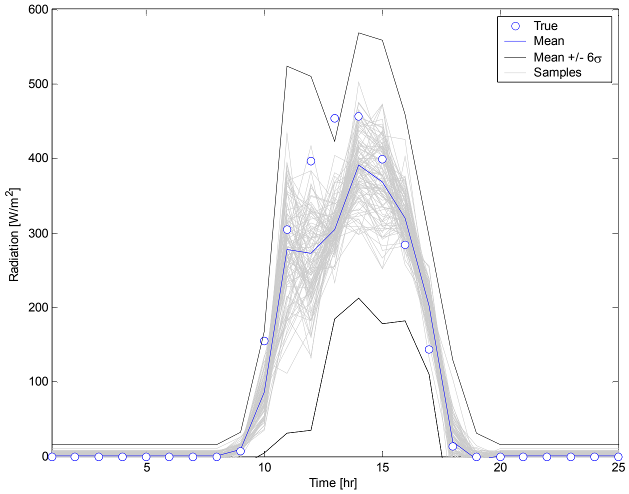

Figure 5. Mean forecast and 100 realizations obtained with the GP model.

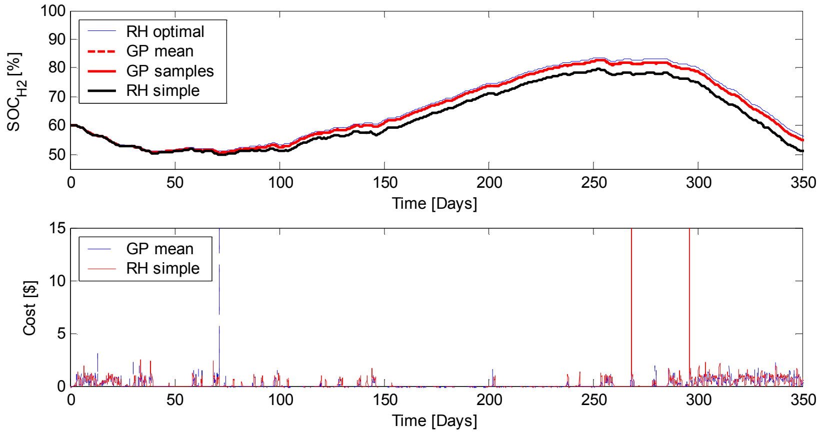

Figure 6. Performance of stochastic RH strategy with GP forecasts.

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